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"Knowledge Management and Skill Needs Anticipation in Labor Market: Toward a Systematic, Dynamic, Interactive and Collaborative Framework to Address Skill Mismatches"

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Abstract

Skills anticipation exercise contributes to address skills mismatches which consequences reach all levels of labour market (Individuals, companies, training and education institutions, countries, and regions). Using a comparative analysis, this paper shows the limitations of current skills anticipation approaches and explains to what extend knowledge management can contribute to address them. There are different qualitative and quantitative approaches to anticipates skills, and each approach presents strengths and weaknesses. Effective skills anticipation relies on effective skills governance guided by some key principle: (i) clear objectives for skills assessment and anticipation systems; (ii) information systems supporting these objectives; (iii) engagement, systematic and active participation of relevant stakeholders; (iv) effective use of the information collected through skills assessment and anticipation exercise; (vi) combination of a variety of methods and addressing technical and institutional challenges. The paper proposes a theoretical systematic, dynamic, interactive and collaborative KM framework to address limitations of skills anticipation approaches.

Keywords: knowledge management, skill mismatch, skill anticipation, skill development, labour market information system

Introduction

Empirical studies on skills mismatch are scarce in Africa owing mainly to the lack of adequate data. However, recent evidence shows that sub-Saharan Africa along with Southern Asia account for the regions most affected by qualification mismatch, which is to a large extent attributable to high incidences of under-qualification (ILO, 2019 cited by IIEP, 2021). Skills mismatches typically result in a number of consequences for enterprises, individuals, and governments many of which may be similar in both formal and informal economies, but the magnitude, persistence and implications may have a particular significance to the informal economy (Palmer, 2021), which is dominant in Africa. Departing from the belief of the economists on the inequality of the labor market, Holzer (2013) assesses the incidence of mismatched skills as something that is always there at any time or decade.

According to the International Institute for Education Planning (IIEP) of UNESCO, the Skills Mismatch in Sub-Saharan Africa is a pervasive and under-researched phenomenon. Sub-Saharan African countries have limited labor market information systems. They most often rely on labor force surveys or other household surveys to analyze the labor market and skills mismatch. Skills-specific surveys are rare and limited to one-off data collection exercises (IIEP, 2022). The demand for data on various forms of qualification and skills mismatches has risen in recent years, in line with the prioritization of countries to ensure that effective policy measures and tools are formulated to improve the quality and relevance of skills formation. Many institutions have stressed the importance of making better use of qualification and occupational skills as a prerequisite for better employment outcomes and employability, as well as improved labor productivity (ITC, 2022). The lack of proper and systematic skills needs assessment and anticipation mechanisms is a major hurdle in Africa's efforts to tackle the skills mismatch challenge. Investing in this domain as part of Labor Market Information Systems (LMIS) is thus of crucial importance. Against this backdrop, the research project aims to contribute to filling knowledge gaps on skills anticipation.

Faced with challenges, it is timely and relevant to conduct a study on the topic ***"Knowledge management and skill needs anticipation in labour market: toward a systematic, dynamic, interactive and collaborative framework to address skill mismatches***". Our research is guided by the following questions:

(i) *What are the key limitations of the current skills anticipations approaches?*
(ii) *to what extent knowledge management can address the current limitations of skills anticipation approaches?*

The purpose is to explore to what extent a systematic, dynamic, interactive and a collaborative knowledge management framework can be used to address some limitations of current approaches of skills anticipation. Natek and Lesjak (2015) assert that in order to improve knowledge management (KM), higher education institutions (HEIs) should integrate their process and data models in conjunction with the KM perspective. Based on this assertion from experts, we will also explore how skill development system can integrate their curricula development processes and data models in conjunction with KM perspective. Specifically, through this research we would like to:

(i) analyze the different approaches and tools of skills anticipation and their related advantages and disadvantages;

(ii) design a theoretical knowledge management framework aligned with the purpose of anticipation of skills needs in labor market;

(iii) identify and analyze the key success factors that can enable knowledge management approach to contribute to skills needs anticipation in labor market.

2. Rationale

Large and persistent skills mismatches lead to significant economic and social costs. This situation means that economies cannot use their human capital efficiently, and many individuals cannot access good quality jobs. Fatih & al. (2020) found that not only does mismatch depress wage growth in the current occupation, but it also leaves a scarring effect—by stunting skill acquisition—that reduces wages in future occupations. Mismatch also predicts different aspects of occupational switching behavior. Low skills perpetuate poverty and inequality. When done right, skills development can reduce unemployment and underemployment, increase productivity, and improve standards of living. Helping people develop and update their skills makes economic sense (World Bank Group, 2022).

Skills gaps are caused by frictions that are prevalent in labor markets. Individuals make education and employment decisions with incomplete information on the economic returns from each alternative. For skills anticipation purpose, governments around the world and many institutions have developed different methods, tools and techniques, ranging from quantitative econometric models to more qualitative methods such as roundtables and focus groups. Therefore, they should be used in a framework of an integrated skills identification system, which provides timely and quality data to inform decision making by policymakers, households and employers (Carolina and Graciana, 2016). Skill mismatches can be reduced by certain policies, however these depend heavily on information about current and future demand for and supply of skills and corresponding mismatche (Breugel, 2017).

Governments and socioeconomic partners in most European Training Foundation (ETF) partner countries are unanimous on the need to develop and better use information on labor market and skills dynamics to improve the performance of education and training, the availability of qualifications and skills for employment, and the lifelong societal and personal development of individuals. In this context, most partner countries have been reinforcing their systems, capacities and methods to identify, analyze and anticipate demand and skills needs in a context of changing economic structures, new types of work, and rapid digital transformation of occupations and tasks (Vaccarino, 2020). In this sense, knowledge management (KM) can play a vital role in capturing, processing, storing, using, sharing valuable information related to skills needs in labor market.

ETF has showed the importance of improving skills anticipation in labor market. Indeed, using a mixed methodological approach in energy sector in Tunisia (combining desk research, data analysis, data-mining techniques and interviews with stakeholders), ETF has provided more nuanced information on emerging skills needs. It has identified the key technologies that will drive skills demand over the short-to-medium-term and the skills that will be increasingly in demand. The results can guide future training provision so that skills shortages that might constrain growth can be avoided. The data collected can also be further refined for additional skills forecasting and foresight exercises (ETF, 2022).

Anticipating skill needs assists informed and strategic choices by policy makers as well as labor market participants, and improves the functioning of the labor market. Availability of skills and access to training relevant to labor market needs are important factors for enabling productivity, economic growth and social inclusiveness. The results of skills needs analysis and anticipation are used widely: by vocational guidance and career counselling; for budget allocations for education and training programs; in the design of occupational and competency standards and training programs; in informing human resource development decisions by enterprises; in targeting retraining programs offered through employment services; in informing policy decisions on the encouragement of workforce migration; as a component of industrial, investment, trade, technology and environmental policies; as an input to national and sectoral employment and skills strategies; and as a mechanism for evaluating training programs and measuring the impact of skills policies (ILO, 2015).

Various approaches can and according to several experts should be used to identify and anticipate skills demand and supply. Cedefop and ETF are just two advocates of the so called holistic approach for skills exercises. Holistic in this context means that all exercises “should be a combination of various methods seeking to achieve robust and reliable results” (OECD, 2016, p. 42). Skills identification and anticipation exercices are undertaken at occupational and educational levels which are considered as skills proxies. Direct skill measurement can prove difficult and for this reason, various countries identify and/or anticipate occupation demand, supply and/or imbalances and use these result as a proxy for the demand, supply and imbalances of skills (Breugel, 2017). In some skills exercises national occupational classifications, and the number of occupational categories are used. Another approach with regards to using occupations as a proxy for skills is to determine the key types of jobs in the domain of interest and then focusing on their occupational structures as they appear from qualitative research. A third approach is using a combination of the previous two: standard occupational classifications where feasible and categories based on qualitative research where the standard classifications do not fit well. Another proxy for skills used frequently in identification and anticipation exercises is education. Proxies for skills related to education are qualification levels (secondary or tertiary), qualification types (general or vocational) and fields of study (law, agriculture, economics, etc.). Again, one approach is to use a standard classification like the International Standard Classification of Education, International Standard Classification of Education (ISCED, 2011) developed by UNESCO.

Skills identification and anticipation exercises across countries also differ from each other with regards to their level of geographical analysis. Most countries perform these exercises at least at national level; however, frequently these nation-wide analyses are accompanied, or in some cases completely substituted, by analyses at state, province or regional level. Executing skills exercises at different levels obviously comes at a cost, especially as some duplication is hard to avoid, but it clearly has its benefits. Fact is that skill exercises at national level benefit “broad training policy and labour market monitoring” (OECD, 2016, p. 45), however, due to their high level of aggregation, they might miss out on considerable differences at sub national level. Put differently, a country’s skills demand and supply might be perfectly balanced at national level, however, considerable regional shortages or surpluses might exist underneath due to labour market mobility within certain regions for example (Shah & Burke, 2005, cited by Breugel, 2017).

3. Conceptual and theoretical framework

3.1. Conceptual framework

DIKW[1]-pyramid distinguishes Data, Information, Knowledge and Wisdom. **Data** is a set of discrete, objective facts about events. It can be defined as raw number, images, words, sounds which are derived from observation or measurement. **The information** represents data arranged in a meaningful pattern, data where some intellectual input has been added. **Knowledge** is broader, deeper, and richer than data or information. Knowledge is information that is organized, synthesized, or summarized to enhance comprehension, awareness, or understanding. "The awareness of what one knows through study, reasoning, experience or association or through various other types of learning" (Mclnerney, 2002, p.1009)[2]. Knowledge is when predictions can be made and actions can be taken, you start to see patterns in the data and information. You no longer look back in the past on what has been, but can start to look ahead and take decisions and act for the future, based on what you know, in real time. **Wisdom** is yet one more step forward, where you forecast implications of decisions and actions (Johansson, 2017).

Generally, literature explores three types of knowledge. **Tacit knowledge:** This type of knowledge is typically acquired through experience, and it is intuitively understood. As a result, it is challenging to articulate and codify, making it difficult to transfer this information to other individuals. Examples of tacit knowledge can include language, facial recognition, or leadership skills. **Implicit knowledge:** While some literature equivocates implicit knowledge to tacit knowledge, some academics break out this type separately, expressing that the definition of tactic knowledge is more nuanced. While tacit knowledge is difficult to codify, implicit knowledge does not necessarily have this problem. Instead, implicit information has yet to be documented. It tends to exist within processes, and it can be referred to as "know-how" knowledge. **Explicit knowledge:** Explicit knowledge is captured within various document types such as manuals, reports, and guides, allowing organizations to easily share knowledge across teams. This type of knowledge is perhaps the most well-known and examples of it include knowledge assets such as databases, white papers, and case studies. KM explores knowledge through two distinctive approaches: personal (tacit) knowledge and codified (explicit) knowledge (Lesjak & Natek 2021). We will focus our analysis on these two approaches.

According to the International Business Machines Corporation (IBM), ***"KM is the process of identifying, organizing, storing and disseminating information within an organization***. Enterprise KM entails formally managing knowledge resources in order to facilitate access and reuse of knowledge, typically by using advanced information technology. KM is formal in that knowledge is classified and categorized according to a pre-specified—but evolving—ontology into structured and semi-structured data and knowledge bases. The overriding purpose of enterprise KM is to make knowledge accessible and reusable to the enterprise[3] (Daniel, 1998, p.54). KM refers to a specific framework to capture, acquire, organize, and communicate both tacit and explicit knowledge of employees so that other employees may utilize them to be more effective and productive in their work thus maximize organization's knowledge (Davenport & Beers 1998).

In this paper, we also consider the official concept definitions from international organizations such as the United Nations Educational, Scientific and Cultural Organization (UNESCO), European Training Foundation (ETF), Organization for Economic Co-operation and Development (OECD), European Center for the Development of Vocational Training (CEDEFOP) and related institute as International Institute for Education Planning (IIEP), and International Labor Organization (ILO). The reason is that their definitions are used in official documents (policies, strategies, programs).

- **Skills mismatches and skills development**

Skill mismatch refers to a situation in which a person in employment, during the reference period, occupied a job whose skills requirements did not correspond to the skills they possess. Skills mismatch

[1] Data-Information-Knowledge-Wisdom pyramid

[2] Claire Mclnerney in Knowledge management and the dynamic nature of knowledge

[3] Daniel E. O'Leary in Enterprise knowledge management

is a discrepancy between the skills that are sought by employers and the skills that are possessed by individuals. Simply put, it is a mismatch between skills and jobs. This means that education and training are not providing the skills demanded in the labor market, or that the economy does not create jobs that correspond to the skills of individuals (ILO, 2020). The ILO has identified different types of skills mismatch : skills gaps occur when the workers lack the skills necessary to do their job effectively; the skills shortages exist when employment cannot find enough professionals with the rights qualification and skills; there is skills obsolescence when workers lose their skills over time due to lack of use or when skills become irrelevant due to changes in world of work; there is over/under skilling when workers have skills above (over skilling) or below (under skilling) those required for the job.

Skills development is the acquisition of practical competencies, know-how and attitudes necessary to perform a trade or occupation in the labor market (European Commission, 2012).

- **Labor Market Information System (LMIS)**

A labor market information system is a network of institutions, persons and information that have mutually recognized roles, agreements and functions with respect to the production, storage, dissemination and use of labor market related information and results in order to maximize the potential for relevant and applicable policy and program formulation and implementation. The main purpose of LMIS is the production of information and analysis for labor market stakeholders. The LMIS can also be directly involved in monitoring and reporting on employment and labor policies. The institutional role of the LMIS can be broadened to include the exchange of information or coordination of the LMIS activities of labor market stakeholders, which include statistical agencies, research agencies and agencies involved in policy formulation and implementation, including and workers' and employers' organizations. The LMIS affects productivity of the labor supply side by providing information needed about changes in skill requirements in specific sectors and may provide career counseling that leads to better occupation choices. LMIS also affects labor market flexibility by having a positive impact on the information flow within the labor market by collecting, evaluating, and providing information to all parties in the labor market. Labor market flexibility and productivity are the main factors of influence on employment and growth (Ghneim, 2018). In this view, KM processes can help provide and organize relevant information to LMIS, and LMIS can provide relevant data, information for a KM perspective.

3.2. Theoretical framework

In the early 1990s, knowledge management (KM) emerged as a formal scientific discipline. KM includes courses taught in the fields of business administration, information systems, management, and library and information sciences (Alavi & Leidner, 1999). There are several methods and applications of KM, and each approach varies by the scholar, author, or practitioner. As the discipline matures, academic debates have increased regarding both the theory and practice of KM, to include the following perspectives (Banerjee & Ray 2015): **Organizational knowledge management theory** primarily focuses on organizational structures and how an organization is designed culturally and hierarchically to manage knowledge and knowledge processes. **Ecological knowledge management theory** focuses on people, relationships, and learning communities, including interactions among individuals and organizations and the internal and external factors that draw people together to share knowledge. **Techno-centric knowledge management theory** focuses on technology and the process of designing technology enablers to help facilitate the flow of knowledge and the storage of information. Regardless of which theory of practice is deployed, knowledge management includes the impacts of people, process, and technology on knowledge sharing.

The paper is based on the combination of the three theories. The reason is that the suggested KM framework focusses on people, relationships, learning communities, including interactions among individuals and organizations and the internal and external factors that draw people together to share knowledge (ecological KM theory) and technology and the process of designing technology enablers to help facilitate the flow of knowledge and the storage of information. Regardless of which theory of practice is deployed, KM includes the impacts of people, process, and technology on knowledge sharing (techno-centric KM theory), and since skills demand is expressed by companies, employers, the organizational KM theory will be useful to how the organizations can manage efficiently knowledge and knowledge processes. Regardless of the school of thought, core components of KM include People, Processes, Technology and/or Culture, Structure depending on the specific perspective (Spender & Scherer, 2007). Rapidly changing technologies have changed the future of businesses, consequently the different roles played by the components of KM; people, process, and technology are yet to be defined in this changed future image. Especially the way organizational knowledge is created and managed in these organizations (Tarek, Rania & Mariam, 2015). For Haddadi Harandi, Bokharaei Nia, and Valmohammadi (2019), the importance of e-literacy of staff in the digital life is fundamentally very crucial, to such an extent that it is considered as one of the primary conditions for successful utilization of KM processes using social technologies within organizations.

4. Comparative analysis and limitations of current skill anticipation approaches

There are a number of available skills needs assessment and anticipation tools that can steer skills development and matching policy more effectively. ILO (2017) and OECD (2016) recognized that there are many approaches and methods developed to identify and analyze current and future skills needs. Each method also has its own strengths and weaknesses. Their use largely depends on the study objectives (qualitative or quantitative), level of analysis (national, sectoral or local), and availability of data and analytical capacities.

4.1. Qualitative approaches and sources

- **Informed opinion and specialist knowledge**

Very useful skills information resides in people such as those working in the industry as employee or employer representatives, education and training providers, qualification agencies, enterprise and trade development agencies, academics and consultants. Various methods are used to extract these individuals' opinions and knowledge such as interviews, either face to face or by telephone, often for the initial round of research. Focus groups of different sizes are used to generate initial ideas and information or to verify and contextualize other studies results such as forecast results from quantitative econometric models. Another information extracting format involving a group of experts, are the workshops. Qualitative questionnaire surveys are another method to be used in case one needs to collect very specific information from a significant number of people in a structured way.

- **Enterprise/Employer surveys**

An enterprise survey is a direct way of collecting information on employment and skills demand by asking firms about their current employment levels, human resource requirements, and anticipated needs, both in the short and the longer run. Enterprise surveys come in various shapes and sizes with less to more attention skill needs and their proxies such as the Enterprise Survey of the World Bank Group, the Manpower Talent Shortage survey and the European Employer Survey on skill needs that has been piloted by Cedefop. Enterprise or employer surveys are highly customizable, are easy to target at one or more specific sectors and can be used to gather both quantitative and qualitative skills information. Its weaknesses relate to the fact that these surveys only focus on direct employment, i.e. excluding indirect and induced employment and thus underestimate actual employment and skills demand; furthermore, it might be challenging to determine its scope, population and sample. And lastly, enterprise surveys might suffer from bias due to selective and/or low response rates or because the shortages witnessed by employers are actually due to a possible unwillingness to offer competitive wages, working conditions or training opportunities on the employers' part (Shah & Burke, 2005).

- **Labor Force Surveys (LFS)**

LFS, are nationally representative household surveys which collect information on employment by industry, occupation, and skill level. Often, they are also representatives at sub-national levels (ILO, 2011, p. 19). The LFS represents a crucial data source in the quantitative approaches to skills and labor markets as sector-occupation matrices are derived from them. The data concern the supply-side of the labour market and as such, the LFS is the opposite of the previously discussed enterprise survey. The most important skills data that labour force surveys tend to generate are the formal educational attainments of individuals working in a certain job, and sometimes overall experience and other measurements of skills are also available. These surveys tend to be held at frequently (yearly) and regularly intervals and run for quite some time, providing time series data. The limitations of LFS are that they cannot provide much "information on insufficient supply of skills, i.e. jobs left vacant because of lack of qualified applicants, or anticipated future demand for certain skills" (ILO, 2011, p. 21). And, although information on the enterprise is collected, i.e. skills demand information could possibly be generated, this information is likely to be more limited than that generated by an enterprise survey due to less in-depth knowledge of individual workers of relevant aspects of the company compared to the company's managers and owners. A final concern regarding labor force surveys is that sufficient sample size is needed to generate reliable results. This is especially important when one wants to analyse skills data across a great number of different occupations and/or sub sectors.

- **Graduate surveys**

Another useful source of information concerning the supply of skills is the surveys held amongst recent graduates. These surveys include not only individuals that are employed, but also the ones that are in further education or training, unemployed or inactive. For the employed, generally information is collected about in which sector and in which occupation the recent graduates are employed. In most countries, the education and training providers themselves survey their recent graduates as they want to know how effective the education provided has been. Graduate surveys are useful in identifying what happens in the graduate labour market, which is useful in validating and improving predictions from models, on the condition that the response is sufficient and that these surveys are executed regularly.

- **Scenarios**

When skills need to be anticipated for the longer term, quantitative projections are less useful, instead constructing scenarios would be a more useful option Scenarios are supposed to be highly descriptive, including an "imaginative exploration of contrasting but plausible futures" (ILO, 2011, p. 110, Breugel, 2017), in other words, scenarios should be used as instruments for a qualitative approach towards skills anticipation. According to scenario advocates, however, it only makes sense to project skills using quantitative models for the first few years of the scenarios as the uncertainty would be too high to deem these models results credible.

4.2. Quantitative approaches and sources

Quantitative approaches for skills anticipation exercises can be classified in two categories: (i) the input-output models and social accounting matrices (SAM) and (ii) the extended versions of the input-output models.

- **Input-Output Models**

Input-output models start with estimates of how the final demand for goods and services, made up of household consumption, government expenditures, capital formation, inventories and exports, will change in the future based on historical data. Then, by using past data reflecting the supply and demand relationships between various sectors in an economy, the model estimates the effects of this final demand change as it works itself through the interconnected value chains of the economy. The input-output models vary in level of disaggregation, i.e. some use a higher number of sectors than others. Models with higher levels of disaggregation allow for more detailed analysis. When the level of disaggregation is not sufficient for the desired analysis, frequently another method, case studies or expert consultation for example, is used to overcome this deficit.

- **Social Accounting Matrices (SAM)**

SAM are basically extended versions of the input-output model as they include "additional accounts for the public sector, taxes and transfers, and household accounts"(ILO, 2011, p. 44). By including these accounts, SAM models are capable of capturing distributive dynamics as they can disaggregate the household sector by household income for example. Furthermore, SAM can be used to look at the impact on taxes and government spending. In sum, the main difference between input- output models and SAM is that the latter includes more types of data than the former. The main output of both Input-output models and SAM are estimates of the changes in output, i.e. GDP[4] and employment, sector-by-sector, produced by a particular sector or a combination of sectors.

Input-output models and SAM are very similar with regards to how they operate and the assumptions used. Both models are empirically grounded, i.e. they are based on historical data on the structure of the economy. Their main assumptions are that *(i) changes in relative prices and possible substitution effects are not considered, (ii) productive relationships are fixed and linear, i.e. they do not change over time and production will increaseproportionally with demand, and (iii) the supply- side is not constrained, i.e. whatever demand,it can be delivered.* These assumptions are both strengths and weaknesses of these types of models. They can be considered as strengths because, although these models are not simplistic, their operations and assumptions are relatively transparent and easy to understand, which makes it easier to assess whether these models are the right ones to use in a certain situations, to validate the plausibility of their predictions and to explain them to policy makers. The latter also can increase policy makers' confidence in the models outcomes. At the same time, these before mentioned assumptions can be considered as weaknesses as it limits the applicability of these models to certain situations such as those in which productive relationships can be considered rather stable and nodisruptive technological changes are to be expected. Another possible weakness of input-output models and SAM is that both are limited by the fact that they can only handle activities that belong to a classified sector. This poses a challenge for countries that want to estimate the employment effects.

- **Computable General Equilibrium (CGE) models**

CGE models consist of a series of equations, each describing certain economic behaviour. At the heart of the model sits an input-output model showing various relationships between industrial sectors and final demand plus a variety of elasticities describing how demand reacts to prices changes. CGE models have several features in common with the input-output models and/or social accounting matrices (SAM) described earlier. CGE models are also empirically based models that estimate how an economy may react to specific policies, new technologies, and external shocks or changes. Like SAM, CGE models may include institutional details that allow studying the distributional effects of policies. And finally, CGE models also have a sectoral structure: detailed linkages between sectors are included and sectors arealso needed to produce skills analysis results. However, CGE models differ from input-output models and social accounting matrices models regarding the role of prices in influencing behaviour and determining economic outcomes which is larger in CGE models, the need for equilibrium conditions to "solve" the equations, and the CGE models' capacity to study the impact of policies onlong-run, instead of only short and medium-term, output and employment growth.

CGE models have several strengths, especially compared to the less complex input-output and SAM models. First, with CGE models a wider range of topics can be studied, such as an exploration of price effects, a detailed analysis of substitution with regard to consumption or productive inputs and significant changes in productive relationships over time. Secondly, by not assuming productive relationshipsto be static, CGE models are more dynamic and therefore can be used to study of long-run impact of policies on output and employment growth. And lastly, when performing sectoral analysis CGE models have the advantage that this analysis is embedded in the larger economy and that inter-sectoral linkages can be explored.

One of CGE models' major weaknesses is the fact that these models are complex and therefore costly to develop. The fact that the models are private property can limit access, transparency and independent verification of the models assumptions. This is because detailed descriptions of the models, including the equations, are not publicly available. It is also more difficult to derive the assumptions from the general descriptions of the model that are available. Another weakness is related to the assumptions and conditions CGE models are based on. In case of the full-employment equilibrium condition, first, one can question the assumption itself and second, this limits these models' capacity to test the employment generation capabilities of policies. However, this weakness might not be as critical as newer CGE

[4] Gross Domestic Product

models can deal with equilibrium unemployment, mark-up pricing, and market externalities. Finally, complexity of CGE models mentioned earlier makes these models harder to understand and explain to outsiders, such as policy makers.

- **Manpower Requirement Approach (MRA)**

One way forecast future skill needs is by occupational forecasting, i.e. forecasting the need for occupations as a proxy for the skills needed. There are several approaches to occupational forecasting which fall into one of the following three broad categories : *(i) extrapolating based onhistorical trends, (ii) using simple regression techniques and (iii) sophisticated econometric techniques allowing interactions between variables.* The most complex and accurate approaches are also the most demanding in terms of funds and professional time required. The best methods in the third and last category are based on the MRA, an approach that has been around since the sixties, however, it has been developed substantially since then into its current form. Occupational forecasts based on the MRA are a valuable addition to the labour market information spectrum for at least three reasons: firstly, "they can identify the implications of existing occupational trends and provide information on the current state of labour markets and expected changes to specific occupations" (Thomas, 2015, p. 26), secondly, they can help policy makers estimate the effects of different policy options on the future level and structure of employment, and finally they serve as input for individuals' decisions on what skills, training and education to invest in. In short, occupational forecasts based on the MRA have a lot of potential.

The weaknesses of the MRA are fisrt of all related to the validity of its assumptions. Indeed, it is often assumed that future participation rates will be equal to current ones and this assumption does not always hold. Another assumption concerns occupational mobility that frequently, for simplicity's sake, is assumed to be non-existent, however, in practice, workers do change occupations. Besides the validity of the assumptions of the MRA model, the manpower requirements approach has been criticized for various other reasons as well. One concern is the lack of accuracy of the results due to measurement errors. A second critique is the separate assessment of supply and demand, as these are known to interact with each other. Thirdly, a tremendous amount of data is necessary for executing occupational forecasts, andthese might not always be available or are too costly to obtain. Another critique relates to the lack of differentiation of worker ability levels within occupations. Finally, another angle of criticism is concerned with certain relationships in the model, like the effect of educational policy on the number of people available for a certain occupation, as firstly, policy can only expand places available for students, but not guarantee that these will be used and secondly, not all occupations have (clear) links to a certain field or level of education. When interpreting occupational projections' results, two other features of the MRA should be considered: firstly, the approach does not take into account any responses from workers, companies nor governments to the results, i.e. the occupational projections show the future of occupations if relevant actors would do nothing. Secondly, by predicting how labour supply and demand will change during a certain period, it is not clear what the total demand and supply at the end of the period will be, as this depends on supply and demand at the beginning of the period.

For CEDEFOP, effective skills anticipation relies on effective skills governance. No single governance model can ensure the effectiveness of skills anticipation as a policy tool, but some principles can help coordinate actors and target groups and processes. These include : clear policy aims; use and ownership of results by all stakeholders; dissemination to ensure wide-ranging impact; sustainable financing. Comprehensive skill strategies (national or regional) that integrate skills anticipation can help exploit its potential. Engagement and participation of stakeholders are crucial, knowing that their roles differ significantly, ranging from systematic and active participation in all stages of design, collection and use of skills anticipation outputs to a consultative role or just receiving the results (CEDEFOP, 2017). Carolina and Graciana (2016) stressesed the fact that an effective system to anticipate skills demand usually combines a variety of methods and surmounts challenges that are technical and institutional. Systems to anticipate skills demand should also focus on building processes to ensure that the information is effectively used in decision making.

5. Contributions of knowledge management

Whatever the approach and the tools adopted to anticipate skills, there is a need for quality data and information to then produce useful information for decision-making that will influence the labor market. Thus, the management of data and information that the stakeholders need to identify and anticipate skills on the one hand, and the management of knowledge resulting from anticipation activities on the other hand, both become essential. KM upstream and downstream of the process of identifying and anticipating skills should play a key role in the detection, creation, conservation, sharing and use of useful knowledge for stakeholders. Without being able to solve the limits of each approach and tools, KM can be useful in capitalization, sharing of good practices, lessons learned. To achieve this, a systematic, dynamic, interactive and collaborative KM framework at the national, regional, sectoral, professional and educational levels is necessary to take into account most of the concerns of stakeholders in terms of skills and occupations anticipation. Such a framework would work effectively under certain conditions as shown in the table 1 below. The combination of the three theories of KM mentioned in section 3.2 is the foundation of proposed KM framework that aims to contribute to address the limitations of current approaches of skills anticipation.

Table 1: knowledge management framework aligned with skills anticipation purpose

Components	Content
Skills identification and anticipation strategy (SIAS) to be prepared and implemented by a multidisciplinary team	▪ Note that effective skills anticipation relies on effective skills governance guided by some key principle: *(i) clear objectives for skills assessment and anticipation systems; (ii) information systems supporting these objectives; (iii) engagement, systematic and active participation of relevant stakeholders; (iv) effective use of the information collected through skills assessment and anticipation exercise; (vi) combination of a variety of methods and addressing technical and institutional challenges*. ▪ Define skills identification and anticipation strategy (vision, purpose, objectives, expected results) ▪ Identify targeted levels (regional, national, occupational, TVET, sectoral ▪ Choose targeted approaches and tools (qualitative and quantitative) ▪ Identify and involve relevant stakeholders (Cross-ministerial collaboration, Social partners, Sub-national and sectoral entities) ▪ Assign specific role to each category of stakeholders
Knowledge management strategy (KMS) to be prepared and implemented by a multidisciplinary team with representatives at national, regional, sectoral, occupation and TVET levels	▪ Set up information systems that support the SIAS and KMS objectives ▪ Determine and analyze strategic knowledge gaps: Knowledge gap, Strategic gap, Relations gap ▪ Formulate the organization's knowledge management vision and objectives ▪ State the knowledge management strategy (personalization and codification) ▪ Specify strategies based on acquisition and development of knowledge in an organization that can be extended to the ecosystem ▪ Identify knowledge management program ▪ Prepare stakeholders for change ▪ Define high level process as a foundation ▪ Determine and prioritize technology needs by assessing what kind of technology will enhance and automate knowledge management activities. ▪ The KM framework needs to be systematic, dynamic, interactive and collaborative ▪ Aligned with the skills identification and anticipation strategy
Skills development system (SDS) governance strategy based on SIAS and KMS	▪ SIAS and KMS are aligned with SDS governance strategy ▪ SIAS, KMS and skill development governance strategies are aligned with the LMIS.

Source : *author design (SISSAO, 2023)*

6. Limitations of study

The main limitation of this research lies in its theoretical nature. Consulting skills anticipation experts and practitioners could have strengthened the comparative analysis of approaches and tools and made it possible to identify possible new approaches.

Conclusion and recommendation

Skill anticipation is unanimously recognized as useful and crucial to provide labor market stakeholders with the relevant information about the skill gap between supply and demand of skill, and to address qualification and skills mismatches. Countries use different approaches and tools to anticipate skills. However, in a context of a very dynamic labor market, and the large amount of data to be collected, the availability of relevant data on a regular and systematic basis remains a real challenge, especially for African countries, most of which have LMIS limited and unstructured. In this context, a systematic, dynamic, interactive and collaborative knowledge management strategy is necessary to identify, collect, process, store, use and share relevant knowledge on current and future skills needs. In this sense, knowledge management using adaptive technologies will be useful to serve skills anticipation.

Given that this paper is more theoretical than empirical, the next step should integrate an empirical component by questioning the stakeholders of the labor market on the establishment of a knowledge management framework that will be systematic, dynamic, interactive and collaborative with the aim to fill knowledge gap on skills mismatches and inform skills anticipation at national level.

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