Investigating an Architectural Framework for Small Data Platforms

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Abstract: The potential of data to support solutions to some of the global grand challenges is uncontested. This potential is recognized and confirmed through the articulation of technology as an explicit Means of Implementation for the Sustainable Development Goals. In particular the advent of big data has introduced not only new data sources and data providers, but also new data analytics and processing algorithms that are having an impact across national and global data ecosystems. The major investments to harness this potential for data are being made in the private sector, to provide insights to inform better decision making for business; and also in the public sector where governments are exploring the use of data for better governance and service delivery. The role of data to make an impact on societal challenges, especially in the context of challenges related to social wellbeing and the Sustainable Development Goals, is typically considered from the macro and meso levels where the trends about national or state/district level phenomenon are observed. This macro level (also called ecological level) perspective, with its associated instruments of analysis, techniques of visualization, is in contrast to another growing perspective which is encapsulated in the small data approach. The small data approach seeks to connect individuals with 'timely, meaningful insights, organized to be accessible, understandable, and actionable for everyday tasks'. Thus within this approach the unit of sampling (which is usually an individual or a household) is maintained as the same unit at which data analysis is undertaken. Consequently the target of consumption of the derived insights and knowledge is the individual, which implies the use of reporting and visualization techniques that are similarly geared at the individuals. This paper revisits an architectural framework for knowledge-oriented, context-sensitive platforms, and evaluates this architecture for the realization of systems and platforms that embody the small data approach. Through a layered and modular separation of data, access, social networking, interaction and presentation components, this architecture seeks to achieve the interaction and presentation personalization for individuals while ensuring not only improved data provenance preservation but also the security of the underlying data.

Keywords: Small Data, Sustainable Development Goals, SDG Indicators, Software Architectures

1. Introduction

The internet technology has heralded one of the greatest revolutions in the history of mankind, associated with it is what has been referred to as the information revolution. This has seen the amount of information and data produced increasing at exponential rates, where more than 2.5 billion gigabytes of data is being produced everyday (IBM, 2013). An increasing number of people are connected to the Internet and active on social media platforms (ITU, 2016). This massive proliferation of information and data has been associated with further structural revolutions to the traditional information industries and societal information systems. One of these changes has been the increased democratization of information production, where initially web 2.0 tools heralded an era of user generated multimedia content, to the current context where social media has completely disrupted: the traditional inter-personal communication, as well news reporting with the increase in citizen reporting and citizen journalism. However beyond disrupting the traditional information systems, wide spread impact and influence of the availability of high velocity, high volume, and heterogeneous data is being felt across all sectors of society (Mayer-Schönberger & Cukier, 2013; Shin, 2016). Businesses are increasingly relying of big data and the associated analytics to inform business decisions and strategy. Similarly governments are also increasingly using data to provide better service delivery and citizen engagement. At the individual level, the advent of smart phones has seen individuals not only being producers of information, ranging from social media chatter, digital traces from online activities, as well as data that is produced from the sensors that are embedded in both mobile devices and wearable computing devices. Another sources of a large amount of data are the IoT devices that are increasingly being deployed in homes, for home automation; in cities, towards the implementation of smart cities programmes; as well being deployed for the monitoring of environmental phenomena.

The role and potential of data to support solutions to some of the global grand challenges is uncontested (World Economic Forum, 2012). This potential is recognized and confirmed through the articulation of technology as an explicit means of implementation for the Sustainable Development Goals (SDGs) (United Nations, 2016). The United Nations 2030 agenda for sustainable development not only makes reference to the role of Information and Communication Technologies (ICTs) to support the implementation of action towards the SDG targets but also recognizes the role of data and big data for supporting the monitoring of the SDG indicators (Letouzé, 2012; SDSN, 2015). At the recently held United Nations World Data Forum there was a showcase of the numerous technology solutions geared towards addressing the pressing issues within the SDG indicator framework(UN, 2016). The most critical of the challenges with the SDGs indicators is the lack of relevant data for some more than 80 indicators (UN, 2016). For this challenge the international statistics community and the data science community are investigating proxy indicators derived from big data to fill the gaps for missing indicators. Similarly alternative sources of data, such as citizen generated data, crowd sourced data, and social media data are being explored as solutions to providing feature-rich (e.g. geo-coded) and disaggregated data for enriching social indicators monitoring, shedding more light, and giving greater insights into the complex human development and sustainable development phenomena (SDSN, 2015; World Economic Forum, 2012).

In the context of the use of data for social indicators monitoring and therefore largely in the context of the SDGs, the focus on the use of data is to typically inform development action and policy at the national level and international level. The typical lenses of analysis and presentation of data is therefore usually framed towards macro and meso levels. Within this framing, the interest is typically towards undertaking brush-stroke observation of aggregate metrics for various phenomena (e.g. poverty, education, health). While this level of framing has its place and context of applicability, it has generally been noted to be limited as far as allowing a nuanced understanding the complex and diverse human and social development phenomena. An alternative framing that focuses on the micro level analysis, and in particular that focuses on undertaking analysis of data at the same unit at which the data is sampled, is the small data approach (Best, 2015). Small data provides a complementary approach to the mainstream big data approaches, and to the approaches that are utilized for social indicators monitoring. There is an increasing mainstreaming of small data approaches wherein efforts are underway to develop analytics techniques, tools and platforms, and architectures and frameworks that encapsulate the small data approach.

This paper presents research that adopts the small data approach for supporting individual and community level action towards the SDGs. In section 2, an overview of the data ecosystem is presented focusing largely on the components (e.g. processes, actors) within the SDG indicators data landscape. The section highlights and hints at the complexity of this data ecosystem and the heterogeneity of the stakeholders and the dependencies between these stakeholders. Section 3 discusses the conceptualization of small data and explores the different notions associated with the concept. This section also highlights the kernel definitions of each of the different conceptualizations of small data. This is followed in section 4 by a synthesis of key attributes of small data from different conceptualization presented in section 3. Section 5 revisits an architectural framework for knowledge-oriented, context-sensitive platforms, and evaluates this architecture for the realization of systems and platforms that embody the small data approach. The paper concludes in section 6 and wraps up with a reconsideration of the potential of data to support solutions to the global challenges, and in particular when both the small data and the traditional approaches are adopted within the data ecosystem. It also concludes with some observations on the suitability of small data architectures and platforms.

2. Data ecosystem for SDGs

Data and information are the key raw materials of the knowledge economy and the use of data permeates many sectors of society. Data exists within a complex system consisting of: different actors who collect and process data, heterogeneous types and sources of data, as well as different consumers and uses of the data outputs. This complex system, represented in **Figure 1**, is supported by data technologies, tools and platforms, standards and protocols.

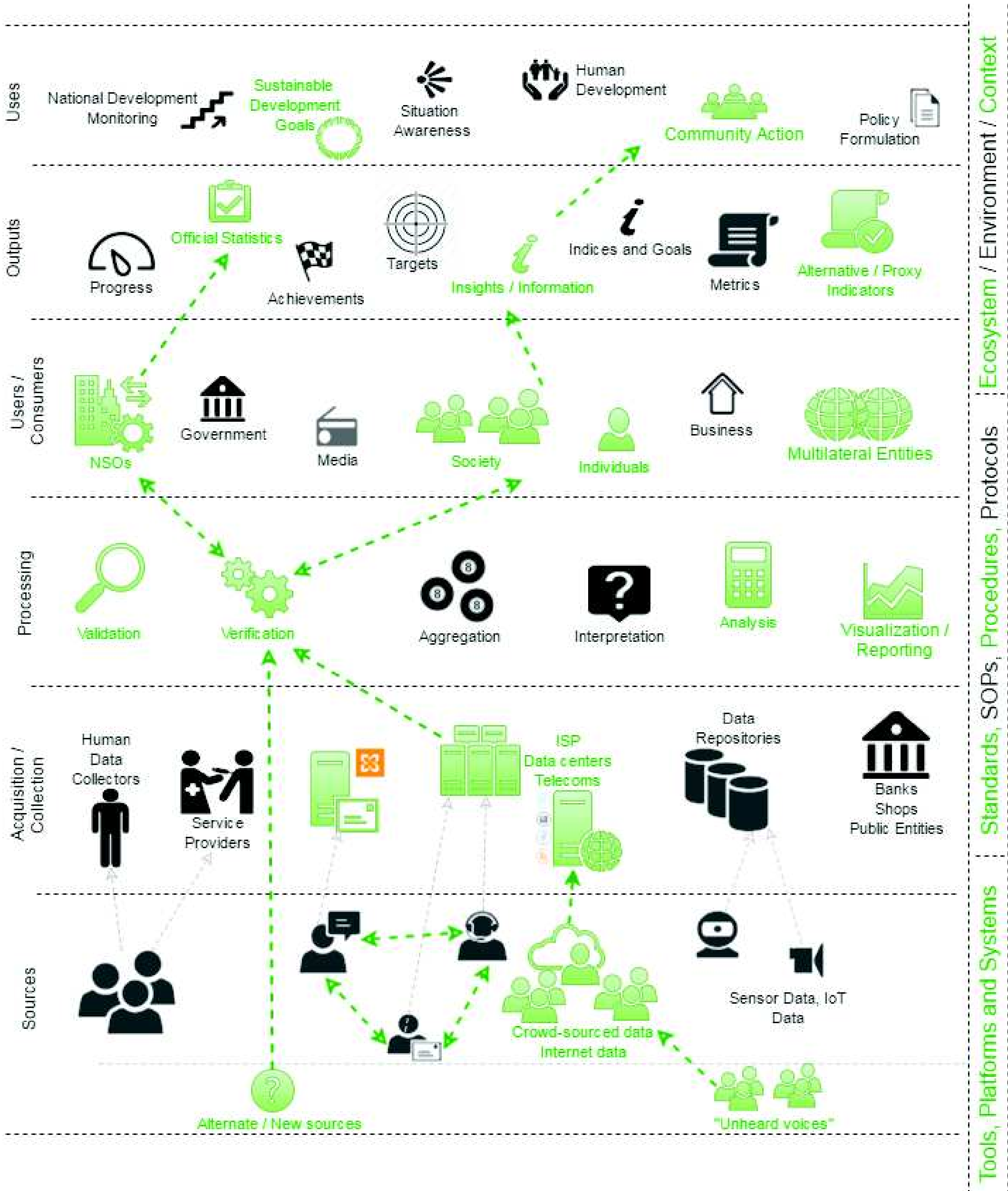

Figure 1: Data ecosystem

Traditionally the collection of social indicators metrics was undertaken purely within the confines of national systems of statistics which were largely under the custodianship of the National Statistics Offices (NSOs). Within these systems, the data production from the national surveys, from administrative data, and including from the census data; the processing and the statistical analysis of the data; as well as the reporting and dissemination of the findings of the analyses, were all clearly defined and congruent with the standard operations of NSOs. The evolution of these systems, which has been heralded largely by the development in ICT and the advent of big data, have seen the introduction of multiple heterogeneous stakeholders, who are involved in the various stages of the social indicators value chain, and who traditionally use the data to pursue various and distinct imperatives. For example, the realization of the rich insights that can be derived from Call Data Records (CDRs) towards informing social indicators monitoring, has mean that mobile telecommunication operators have become one of the important potential stakeholders towards the monitoring of social indicators. Mobile telecommunication operators collected data primarily for informing business strategy and decisions, and the data they collect represents a critical business asset which they monetize.

The need for these different stakeholders to cooperate within this new data ecosystem is necessitating an investigation into the relevant partnership models, data sharing standards and protocols, data platform architectures and frameworks, for utilization and application within this data ecosystem. Besides the introduction of new stakeholders, this new data ecosystem is also characterized by the new sources of data which would have not been traditionally used for social indicators monitoring. These include crowd-sourced data, citizen-generated data, sensors (i.e. IoT) data, and other digital data sources. Each of these data sources presents a unique set of requirements in terms of processing, validation and verification, as well as analysis; and the combination and mixing of these different data sources represents an opportunity for unique synergies to be realized.

Another eminent evolution of the social indicator data ecosystem, corollary to the introduction of a multiplicity of stakeholders, is the increased democratization and decentralization of the social indicators monitoring. While the production of the official social indicators metrics might remain the ambit of the NSOs for a foreseeable future, the reality is that numerous stakeholders are already involved in collecting, processing and producing social indicator data. This has included the use of data for the monitoring of disease outbreaks (Carneiro & Mylonakis, 2009; Lazer, Kennedy, King, & Vespignani, 2014), situation awareness around natural disasters (Shelton, Poorthuis, Graham, & Zook, 2014), as well as other numerous societal wellbeing phenomena (Procter, Vis, & Voss, 2013). The role of individuals within the data ecosystem is also set to be emphasized as there is increasingly more advocacy for improved data provenance preservation, data ownership attribution, and privacy and confidentiality enforcement. The emphasis of the individuals within the data ecosystem is also driven by the increasing realization of the need for the collected data to be disaggregated and collected at a fine level of granularity, i.e. the individual level. This perspective that focuses on the micro level, bottom-up, individuals social wellbeing phenomena is encapsulated in the notion of small data – which is complementary to the traditional top down, macro level perspective in social indicators monitoring.

3. Small Data, by any other name?

Small Data is a term that is gaining traction not only in academic circles but also in business and in popular culture. The emergence of the term in academic publications can be noted since around the turn of the century, and this is suggested by the observation from the number of publications with the terms “small data” in their title from the Science Direct library (**Figure 2**). While the term has been noted in publications as early as 1989, the bulk of the earlier publications used the term to refer to small datasets typically from the domain of statistical mathematics, as opposed to the more recent variations of the term “small data” which are defined within data and information sciences domains.

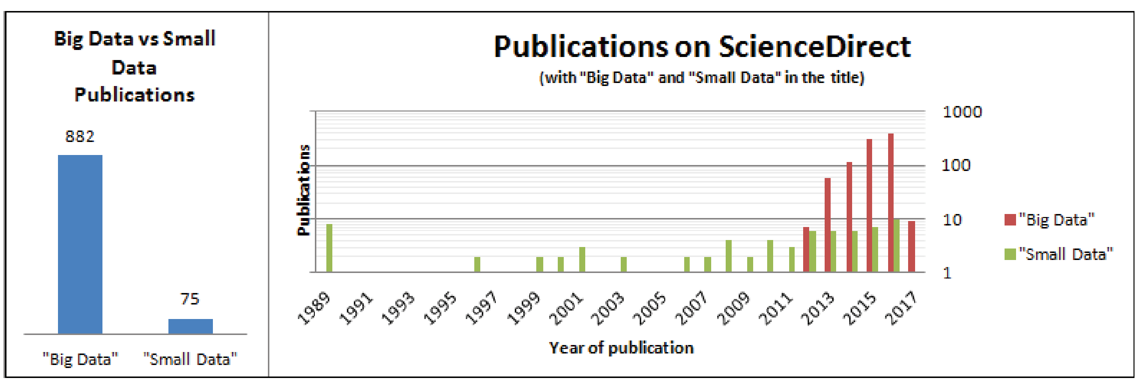

Figure 2: Prevalence of "small data" publications

There are currently a number of distinct notions of small data that present different perspectives on the definition and characterization of small data. As such the small data discussions and deliberations are currently muddled in not only the heterogeneity of definitions but also in the clash of perspectives. This situation is not too different from that experienced around the evolution and contestation of other terms and concepts. For example, in the case of big data, until the clear authoritative articulation of the 3 V’s (Douglas, 2001) of big data and subsequently the 5 V’s of big data, there was a similar muddling up of the terms (Philip Chen & Zhang, 2014; Ward & Barker, 2013).

The subsequent sections discuss some of these prominent articulations and notions of small data:

3.1 Small data as small data sets

One of the notions of small data that hasn't gained much popularity is that which refers to small datasets. This notion has its roots in statistical mathematics where the study of small dataset is well established. This perspective takes the "small" in small data to refer to the size of the datasets that are being utilized and operated on. While no clear stipulation is being made on the characteristics of these datasets for consideration as small data, the typical framing is to juxtapose these with the well defined attributes of big data. Therefore in this sense small data would be data that is not of high volume, reasonably homogeneous, and that is not of high velocity. This notion therefore alludes to small data as data that can be processed with standard desktop computing infrastructure and that doesn't require any of the new technologies that need to be deployed for big data.

3.2 Small data as actionable by-product of big data analytics

There is notion of small data to simply refer to the information and insights that are generated as a product of big data analytics. This perspective contrasts the low utility of the raw big data, with its high volume, increased variety, and high velocity (along with value and veracity) against small bite-sized actionable insights and information – which are termed small data. The term that is sometimes used in this sense is that small data is "the last-mile of big data" (Dale, n.d.). This focus on the resultant utility of the data is articulated eloquently by Bonde where he notes that "small data connects individuals with relevant, timely, meaningful insights, organized and packaged to be accessible, understandable, and actionable for everyday tasks" (Bonde, 2013).

3.3 Small data where n = me

Another notion of small data refers to the digital traces that individuals leave behind during their action and interaction with digital/electronic products – typically mobile devices. This notion of small data refers to the similar type of data which is termed data exhaust in the Global Pulse taxonomy of big data (Letouzé, 2012). This perspective on small data goes beyond defining small data in terms of the nature of the data, but rather based on the processes of data analysis that are adopted. The emphasis in this notion of small data is that the application of the tools and platforms developed in this context is focused on the individual (and therefore the notion of n = me) consumption and utility (Estrin, 2014).

3.4 Small data from ethnographic human-centric observations

One of the most recent notions of small data is contributed from the business and marketing domain, and has been popularized by the book "Small Data: the tiny clues that uncover huge trends" (Lindstrom, 2016). This notion of small data is almost directly orthogonal to the current big data approaches in that it emphasizes the importance of targeted ethnographic observations to gain key actionable insights about a phenomenon. This technique has been used successfully to assist corporations to gain better insights about their products and their customers, and it has in particular been juxtaposed with the big data approaches that, in the specific cases of some of these corporations, had failed to yield key actionable insights. A critical aspect of this approach is that it relies on the ability of the investigator to be embedded within the household of study and through keen observation and personal insights to piece together the small clues to better understand key phenomena under study. This approach recognizes the importance of the context and the systemic dependencies for understanding and interpreting individual observations.

3.5 Small data as an approach to data analysis

Some of the definitions of small data highlighted above regard the quantity of the data processed as well as the loci of collection of the data. Best proposes small data as an approach to data analysis wherein the unit of analysis of data is congruent to the unit of sampling of the data (Best, 2015). Thus if data is sampled at the unit of a household or a city, then the analysis and comparative evaluations are similarly undertaken at the household and city level respectively. When applied to data that is collected with individuals as the unit of sampling, this approach emphasizes the potential of data to be more relevant, insightful, actionable and empowering to the individuals themselves. This approach takes into consideration the well known quality and reliability issues that are associated with deriving ecological insights from individually sampled data (Oakes, 2009; Piantadosi, Byar, & Green, 1988). Small data as an approach to data analysis can therefore be applied without limitation to data that is traditionally termed big data (i.e. high volume, high velocity, and high variety) as much as to alternatively sourced data, such as crowd-sourced data, citizen generated data, as well as other types of digital data (Letouzé, 2012).

4. Small data synthesis and amalgamation of concepts

The notions of small data noted above highlight varied perspectives with emphasis of different aspects of the nature, processing and utilization of data. These notions share overlaps and commonalities, and similarly have key kernel meanings that differentiate them from the other. While in one instance the first notion (section 3.1) focuses on the what (i.e. small size and quantity) of the small data, in another instance Lindstrom's notion (section 3.4) focuses on the how of the collection and processing (i.e. through embedded human-centric observations) of small data. On the other hand Estrin's notion (section 3.3.) of small data exclusively focuses on the individual, and the digital traces data that is associated with the individual, to increase utility for the individual. In comparison, Best's notion of small data (section 3.5) rather focuses on analysis and utility of data at the same unit as the sampling, and in this sense it therefore encapsulates and supersedes Estrin's notion, where the unit of sampling and data collection is the individual. Bonde (section 3.2) emphasizes the utility of data and the need to make data actionable for everyday life.

The key contributions from these different notions of small data, applied to social indicators monitoring are as follows:

1. **Focus on individual** – the focus on the individual for the collection, analysis, and reporting is a theme that is echoed in four of the notions of small data above, except in the notion of small data as small datasets. Social indicators monitoring largely collects development and wellbeing data from and about individuals. This therefore gives a strong alignment with both Best's (2015) and Estrin's (2014) notion of the focus on the individual for the analysis of the data and the resultant utility of the derived insights.
2. **Heterogeneous data** – the realization that small data comprises data from multiple sources including big data, crowd-sourced data, citizen generated data, and sensor data, is shared across at least three of the notions of small data above. This therefore places no restriction on the type of data that is collected as a defining feature of small data, but rather recognizes that relevant wellbeing data about an individual is heterogeneous and multi-faceted. Illustratively, data from wearable computers and activity trackers, can be combined with data from IoT devices (e.g. a smart scale, or a refrigerator), along with perception data from social media, to establish the health and wellness of an individual.
3. **Context-bound data** – this attribute is emphasized largely from the perspective that the understanding and interpretation of data is tightly bound to the context from which the data was collected (Lindstrom, 2016). This context comprises not only the socio-cultural environment of the individuals, but also the environmental and other context factors associated with an individual.
4. **Data provenance** – this is an attribute of data that allows for the establishment of the genealogy and history of the data. While this as a requirement is not explicitly articulated as an aspect of the definition of small data above, it is implicit in the characterization of small data as context-bound (section 3.4), focused and attributable to individuals (section 3.3), and analysed at the unit of the individual (section 3.5). Data provenance is an attribute of small data that is motivated by the emphasis of the individual as the owner of their data, and therefore necessitating an ability to trace the genealogy of the data throughout its processing and evolution.
5. **Everyday data utility** – this is an emphasis that the outcomes of the small data value chain should accrue towards individuals and their everyday wellbeing. In this sense small data should connect individuals with the insights and the information that is immediately actionable towards their development and wellbeing. And defined more formally with insights from Sen's Capability Approach, small data should connect individuals with insights and information that increase individuals freedom to achieve the desired functionings (Sen, 1999).

These attributes provide an amalgamated conceptualization of small data which is derived from some of the current notions of small data in literature. Therefore the overarching kernel meaning of small data is an approach to data processing that focuses on the individual as the loci of data collection, analysis, and utilization towards increasing their capabilities and their freedom to achieve the desired fuctionings. This notion, characterized by the attributes itemized above, is the one that is adopted in this research and based on which the hereafter discussion on small data architectures is framed.

5. Revisiting the PIASK architecture

Software architectures play a critical role of defining fundamental components and structure of software systems allowing for component reuse, better analysis, and for developing a common understanding between the different stakeholders involved with the software development and use. This section revisits PIASK, an architectural framework for knowledge-oriented, context-sensitive platforms, and considers the suitability of this architecture for the realization of systems and platforms that embody the small data approach (Thinyane, 2009). PIASK, which is a named acronym from the Presentation, Interaction, Access, Social Networking, and Knowledge Base components of the architecture, is motivated by the goals of:

1. Provisioning of an end-user device agnostic interface to the underlying data to allow for handling of requests from heterogeneous devices
2. Allowance for varied and multiple interaction modalities with the users
3. Encapsulation of local knowledge and the emulation of local knowledge system dynamics to allow for a seamless exchange of knowledge in real life and on the virtual platforms – informed by Nonaka and Takeuchi's SECI model (Nonaka & Takeuchi, 1995).
4. Handling of multimedia data
5. Embracing of current knowledge engineering standards and service oriented architectures principles

The architecture addresses these goals through defining 5 key components/layers. These layers are (Thinyane & Terzoli, 2011): the knowledge base layer (which encapsulates the associated data and knowledge of the individual); the social networking layer (emulating the social systems within which the individual participates); presentation layer (handling the primary interfacing to the users in a manner that conveys the user's aesthetics, preferences and sense of beauty and form); the access layer which handles the interaction with the multiple heterogeneous devices; and the interaction layer handles the interaction based on the users' preferred usage modality. The architecture is primarily a layered architecture as evidence from the partitioned dependency structure matrix in **Table 1**

Table 1: PIASK Partitioned Dependency Structure Matrix **(Thinyane & Terzoli, 2011)**

		1	2	3	4	5
Access	**1**					
Interaction	**2**	**X**				
Presentation	**3**	**X**				
Social Networking	**4**		**X**			
Knowledge Base	**5**		**X**		**X**	

In considering the suitability of this architecture for the implementation of small data platforms, a conceptual mapping of the key small data attributes (defined in section 4) is made onto the five layers of the PIASK architecture in **Table 2**. This initial high level mapping allows one of observe the alignment of the PIASK architecture with the key attributes of small data.

Table 2: Mapping of PIASK layer to small data roles

Layers	Description	Small data role / attribute
Presentation	Interfacing with the user, rendering visualization and UI components	Adaptation and personalization for individuals
Interaction	Primary business logic and platform functionality implementation	Data Processing, Small Data Analysis
Access	Interaction with multiple heterogeneous devices / data sources	Heterogeneity
Social Networking	Embedding within social context	Social Context embedding
Knowledge	Data and knowledge storage	Domain Knowledge, Ontologies, Data Provenance, Meta-data

6. Conclusion

The role and potential of data towards addressing the global grand challenges is uncontested, and is acknowledged in the 2030 Agenda for Sustainable Development. This paper advances the small data approach as necessary and complementary to the largely emphasized big data approach, especially as applied to social indicators monitoring. The key kernel attributes of small data, applied to social indicators monitoring, is the emphasis on the individual, their data, and the analysis of the data to be actionable at the level of the individual, with the secondary imperative of informing macro-level understanding of various social phenomena. The operationalization of the small data approach, through the implementation of relevant ICT artefacts for empowering individuals and community level actors towards the achievement of the SDG targets, is an ongoing activity associated with this research. As an initial phase towards the implementation of these ICT small data artefacts, this paper has revisited and considered the PIASK software architecture for suitability and relevance. The mapping of the key small data attributes to the five layers of the architecture shows initial alignment and potential suitability of this architecture for the subsequent implementation of the small data tools and platforms.

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