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Digital Web Ecosystem Development for Managing Social Network Data Science

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Full research paper

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Abstract

The World Wide Web (WWW) unfolds with diverse domains and associated data sources, complicating the network data science. In addition, heterogeneity and multidimensionality can make data management, documentation, and even integration more challenging. The WWW emerges as a complex digital ecosystem on a Big Data scale, and we conceptualize the web network as a Digital Web Ecosystem (DWE) in an analytical space. The purpose of the research is to develop a framework, explore the association between attributes of social networks and assess their strengths. We have experimented with network users and usability attributes of social networks and tools, including misgivings. We construe new insights from data views of DWE metadata. For leveraging the usability and popularity-sentiment attribute relationships, we compute map and plot views between instances of technology and society dimensions, interpreting their strengths. Visual analytics adds values to the DWE meta-knowledge, establishing cognitive data usability in the WWW.

Keywords: Digital web ecosystem, heterogeneity, WWW, social network science, Big Data

1 Introduction and Motivation

The complex systems inherit multidisciplinary domains with sets of data entities, dimensions and objects. The collaborations, interactions, relationships and dependencies are ambiguously interpreted between data sources (Barrat et al. 2004; Bar-Yam 2002). The WWW manifests with data sources in volumes and varieties in multiple domains. Each domain may have several attribute dimensions that may emerge on an ecosystem scale as DWE. Heterogeneity of data is an added challenge while modelling the DWE and its artefacts. In DWE, the tech (technology) concepts and tools, including various social networks and search engines, interlink digital media in an analytical-knowledge space. Each attribute dimension is connectable to other systems with specific domain checks and constrained business rules. The existence of multiple systems, their linked attributes has motivated us to develop a DWE theory.

In addition, complexity in a network of networks may be ubiquitous with dependent relationships, interfaces and behavioral aspects (including chaotic relationships) in the DWE. A holistic data modelling technique is needed for modelling intricate network systems, such as DWE. With the manifestation of complex data systems, the modelling approaches must inherently offer ubiquitous contexts in relationships between attribute dimensions. Eventually, the commonalities created among multifaceted attributes motivate us to explore connections with cognitive and creative relationships through multidimensional models, easing the complexity of systems. To understand the connectivity of social networks with populated masses, we need to take the help of new IS articulations and examine their services in terms of digital transformation, business growth, market values, people perpetuations and knowledge-based information solutions. The research aims to ascertain the connectivity between types of users, usability properties, data breaches, revenues made by social networks, including users' behaviors. The connectivity is knowledge-based conceptualization with multiple associations and dependencies (Shanks et al. 2004; Wu and Davison 2006). The authors in Davidson and Moss (2016); Plastria et al. (2008); Shanks et al. (2004) describe various star and snowflake schemas to collaborate with geographic contexts of ecosystems. Several such data artefacts articulated in logical and physical data schemas in ecosystem scenarios are interpretable as in Moody and Kortink (2003). The connections and actions are difficult to model due to dependencies and relationships, represented as interactions between ecological systems (Burke 2013). The properties such as nonlinearity, emergence, and spontaneous order, adaptation-, and feedback loops emerge while presenting relationships between entities and attribute dimensions of the DWE (Bar-Yam 2002; Patel et al. 1999). In addition, the semantic descriptions as given in Maguitman et al. (2005); Reagans and Zuckerman (2001), are manageable during interpretation of nomenclature and vocabularies associated with the content, the meaning of dimensions deduced in the DWE, ensuring that without any ambiguities or inconsistencies the attribute dimension models convey knowledge, adaptable in the DWE scenarios (Zhu et al. 2020). In this context, we underline the association of computer programmers and ontology designers to perceive and incorporate the design aspects and requirements for categorizing dimensions and their levels, including overall hierarchy descriptions needed in the DWE.

Interpretation of interaction and connectivity between diverse domains is a prerequisite in the development of DWE. The value of network science and its analytics cannot overlook analysis of various research elements and processes of the ecosystems. Various elements and processes existing in the WWW are not examined in human ecosystem contexts. The DWE, in the research, inhabits large geographic and demographic regions worldwide, holding many geographic-based realms with numerous interconnected Information Systems. However, previous research lacks an explicit cognizance of the connectivity between systems, which is pivotal for investigating the DWE and its evaluations in human-computer interaction perspectives. The human-computer interaction has inadequacies, establishing the growing discernment of multidimensionality and heterogeneity of data sources in the DWE contexts (Karhu et al. 2011).

The article is structured as follows. The DWE and its heterogeneity in social networks are introduced in Section 1, including various components of social network informatics. The literature survey and the present limitations of the web frameworks are presented in Section 2. Based on the research gaps, research questions and objectives are designed in Section 3. In Section 4, the theoretical framework of the DWE is developed with its relevance in social network informatics solution development. Analysis and discussions are made in Section 5 with the interpretation of DWE data cubes and their data views. In Section 6, the significance and contribution are discussed, how the DWE framework can change social fabrics of the WWW and its usability. Section 7 concludes by interpreting the resilience and sustainability of the DWE framework in societal contexts.

2 Previous Research and Limitations

We explore the research gaps existing in the literature in this section. Logically, digital ecosystems can be associated with Big Data sources at multiple nodes that create inherent connections or interactions between domains and systems (Keme et al. 2010; Reuven and Havlin 2010; Sivarajh et al. 2017). In addition to conceptualization, the connectivity attributes at places are contextualized in spatial-temporal domains, construing thousands of entities and dimensions (Barrat et al. 2004). The DWE, as a social network framework, makes connections based on data relationships with shared interests and concerns. Various components, described as social network tools in the DWE, have gained great attention in different applications such as search engines, communication technology, social informatics and organizational management. Network tools are usable in the socio-cognitive analysis of email links, including social informatics solution management (Srivastava and Gupta, 2014). Various hypotheses are analysed in social networks (SNA) using various network tools and technologies and focusing on food security (Popp et al. 2018). Different applications of human and environment ecosystems are discussed in bio-diverse environments, with evaluable ecosystem measurements (Garrett 2009). Social Network Analysis (SNA) techniques and their applications are described with the perceivable structure of the social network (Srivastava and Gupta 2014). They examine strengths, weaknesses, opportunities and threats of social networks that curtailed usage of the Internet. The researchers rationalize Online Social Networks (OSN), probing the structure of social relationships in a group to uncover the informative connections between people. Various network measures are described as demographic diversity and network heterogeneity (Reagans and Zuckerman 2001). They develop a theory based on network density and social capital with different hypotheses on structural holes, including demography and productivity. The authors in Cameron and Trivedi (1998) collaborate a theory to practice with various types of data and share research in applied statistics, econometrics, marketing, operations research, demography, biostatistics and quantitative social sciences. The topological architecture of weighted networks is evaluable with heterogeneous connections, which are in the form of relationships between contexts of technological, transportation infrastructures, social phenomena, and biological systems, considering centrality and its weights (Barrat et al. 2004).

The authors have analysed network usability analysis using ensemble techniques in social applications (Araque et al. 2017). The concept of a digital ecosystem is described as a counterpart of biological ecosystems (Briscoe 2009). They emphasize the digital ecosystem as self-organization with ecosystem-oriented architecture optimization. Implementation of ecosystem articulations is challenging in societal and business contexts (Eamonn 2016). The concepts of digitization and ecosystem are collaborative, keeping the pace of the industrial economy, besides managing the societal challenges on networks, in which business models affected their implementations. Both technology and business service aspects are described using concepts of the digital ecosystem and its related conceptual models (Moody and Kortink, 2003). For creating conceptual models, the authors explore case studies using various apps from smartphones and bioinformatics service registry BioCatalogue. The co-creation value is unifiable with digital ecosystems; how the integration process influenced the consumer-firm interaction and its impact on businesses (Negi and Brohman 2015). The authors characterize the digital ecosystems based on goods and services with sources of innovation management. A systematic review of technology-guided ecosystems is done in real-world scenarios with platform-centric architectures (Marcos-Pablos and Garcia-Penalvo 2019). Big Data and business analytics are proposed for digital transformation in sustainable societies, the so-called Digital Transformation and Sustainability (DTS) model (Pappas et al. 2018).

3 Research Questions and Objectives

The introduction and literature survey have motivated us to draw research questions and objectives. The DWE, which is inherited from interconnected data relationships, is interpretable with several attribute dimensions. They are connectable in a holistic framework, as articulated in a repository system through multidimensional schemas. We have initially chosen *Search Engines, Social Media, Tech Concepts, Tech Tools, Smart Phones, Network Technologies, Online Utilities, e-commerce and Emails entities*, and their attribute instances of the Digital Web Ecosystem. But, we have focused on tech concepts, social media and search engines entities and their attributes in the current research. The DWE is evaluated as multidimensional repository. To make the repository more adaptable, we aim at designing fine-grain data artefacts with different knowledge-based entities and attribute dimensions. One of the core research objectives is resolving the heterogeneity of the data sources in multiple domains of DWE. To uncover and understand the impacts of technology in societal web ecosystems, we aim at the following research questions and objectives:

1. What are the components of the DWE in the social network and technology contexts?
2. How do we evaluate the DWE and manage the network data science?

The purpose of the research is to uncover patterns of relationships and analyse the affected societal attitudes and behavioral challenges by way of technology use, its adoption and diffusion in the web-based digital ecosystem applications and their components. We design the following research objectives with their significance:

1. *Articulate an integrated* DWE *framework development:* For discerning the relationships between technology and society, we need to identify and examine the adaptable attributes of the DWE. Design and develop artefacts with connectable relationships through domain ontologies with an explicit description of naming conventions and terminologies, including their axioms.
2. *To enable the use and reuse of domain knowledge in DWE:* Data views extracted from warehoused metadata represent diverse knowledge domains. The knowledge-based domain ontologies are specialized artefacts (Nimmagadda et al. 2021) in the integration process. The spatial-temporal dimensions are typical in modelling multidimensional ecosystems and evaluating their associations in DWE contexts.

A common understanding of the structure of information and knowledge is shared. We articulate a mechanism that the DWE and its artefacts are interrogative and exchange information among multiple applications to associate and share any new knowledge in various contexts. Besides, the IS artefacts the way they are presentable depend on data types, size of data, including data characterisations. However, colourful artefacts cannot guarantee new insights, but graphics can convey information with visual aids.

4 Development of DWE Theory

Conceptualized as an ecosystem (DWE), the digital web offers various online services with technology concepts and tools. The concept further emerges with benefits to diverse communities and deliver quality health and prosperity with evaluable measures. In such contexts, informatics solutions are reshaping their pathways to offer technologies, tools, and best practices for the growth of web-linked social networking services. Transmission of multimedia content enables us to bring information together to larger diverse communities through Google, Facebook, video conferencing tools, especially in global pandemic-health environments. The DWE can pave a way to connect the disconnected societies, substantially reducing the cost of communications among diverse users worldwide. We provide new construct modelling methods and integrate the constructs in an architecture in which the ecosystem is described from concept to development. A framework is articulated with medical informatics solutions with multi-institutional collaborations in geographic dimensions. They underpin the communication technologies in cognitive, sociocultural and logistics contexts (Araque et al. 2017).

A knowledge-based digital ecosystem unfolded as an integrated framework is a requirement for managing various ecosystems that offer internet services. Google engages a large part of Internet search engines. We have carried out experiments with periodical analysis of usability and popularity sentiments using Google trends for more than 60 websites that involve search engines, social networks, tech tools and concepts and their applications. For building usability data relationships in multiple dimensions of the *DWE*, we examine data sources and present granularity of data in the form of fine-grained data structures. The granularity rests on fine-grain data structuring to represent digital ecosystems and their embedded systems explicitly, assessing the value of integrated workflows in multiple domain applications of the DWE. We enumerate 1-3 Items with various tasks in the workflow, from data acquisition to new knowledge interpretation (Nimmagadda et al. 2021). Web ecosystem hosts several systems, sub-systems, domains, types and sub-types with numerous entities and dimensions (Reuven and Havlin 2010). Various tech tools and concepts are data-, domain- and system-centric. They vary in multiple scopes, in particular in spatial-temporal dimensions. It is trivial to speculate about the relationships between technology and society without understanding their dependencies in spatial dimensions. We need to examine the technology trends in spatial dimensions and elucidate their relationships between dimensions of technology and societal contexts. In addition, we explore the Web by carrying out experiments and data analytics on DWE metadata and envisaging new insights from the interpretation of WWW. The current challenge is to explore and exploit the technology trends, users, and usability sentiments among interconnected social ecosystems.

- DWE *complexity:* It is due to the existence of several interconnected and interdependent domains and systems.
- DWE *as a network of networks:* The DWE workflow attributes with connectable arrays of schemas, making links between systems and domains logical and operational through digital media.

- DWE *offers non-linearity solutions:* Non –linear and nonaligned systems can be ascertainable with coordination of ecosystem conceptualization and contextualization. These features inherit from the existence of multidimensionality and heterogeneity of data sources in spatial-temporal dimensions (Nimmagadda et al. 2021).
- DWE *emerges with concepts and contexts:* The conceptualization and contextualization features may have emerged with new attributes and their instances in new knowledge domains.
- DWE *must be adaptable in new emerging concepts and contexts:* New schemes of DWE must be adaptable with new business rules and constraints, as they emerge periodically in multiple domains.

The evolving concepts and contexts are reexamined, ensuring embryonic connectivity with adaptable relationships between technology and societal attribute contexts. We make sure to build models so that amendments are logical and manageable in new knowledge domains. An ecosystem is a composite organization whose members benefit and reconcile each other's participation via symbiotic relationships through positive-sum relationships (Thomas et al. 2006; Wand 2000). We put rigor on design and data science views of an ecosystem. To understand the inadequacies and affix the research gaps on technology-guided web ecosystems and their associations with large-scale societal systems, we analyse various entities and dimensions of the existing models of web ecosystems and reexamine the proposed new model articulations. The framework discussed performs various task entities, as narrated by items 1-9. The data acquisition, identifying the data for entities, dimensions, attributes and relationships. Several ontology structures are designable for Big Data attribute dimensions, for which mapping and modelling are crucial tasks of the framework (Ding and Fensel 2001). Various rectangular boxes are drawn, explaining the tasks. The selection of a specific data schema is based on the data type and user need criteria. Data warehousing and mining, with visualisation and interpretation, are critical tasks of DWE data science.

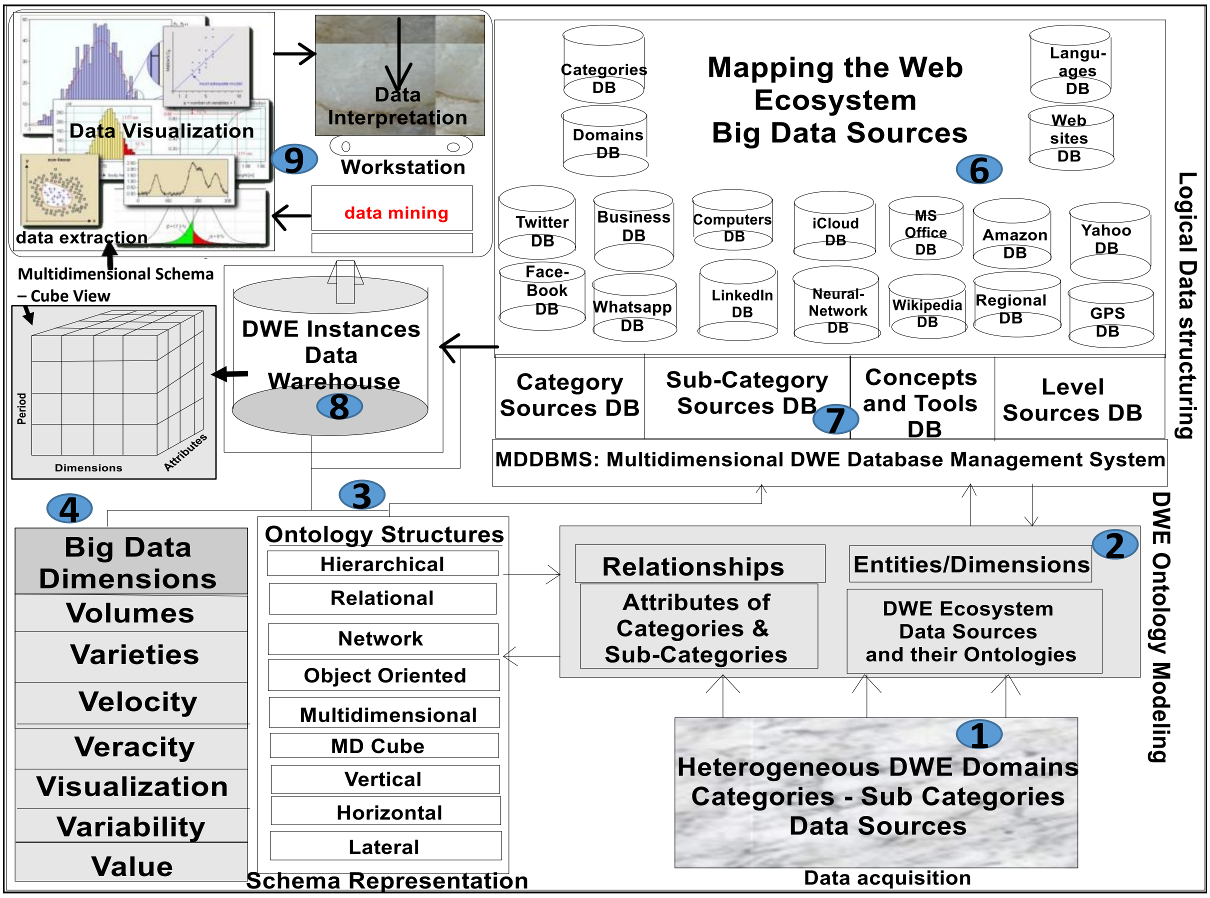

Figure 1: A framework representing the Digital Web Ecosystem (DWE) (Research Objective 1)

Entities, dimensions and objects are crucial elements and building blocks of an ecosystem. Multiple systems and different domains related to societal and technology events are part of the web framework DWE. Various data considered from secondary sources (Garrett 2009; Kemp 2019) are manageable through IS articulations of the integrated framework deduced in Figure 1. As shown in Figure 1, the DWE is a conceptual framework to quantify system elements, patterns and processes and manage web resources through collective activities and their interaction in spatial-temporal dimensions. Subsequently, the interactions between societal structures and various activities driving the DWE have enabled us to rationalise this strategic ecosystem development. Different stages enumerated in Items 1-4 and 6-9 in the framework architecture in Figure 1 describe activities from data acquisition to the data interpretation stage. Items 1-4 represent data acquisition and data structuring stages; items 6-7 represent the data mapping and modelling process. Items 8-9 describe data mining, visualisation and interpretation artefacts of the framework. We investigate several entities and dimensions in the DWE to construct multidimensional schemas, including numerous conceptualized and contextualized features. They are construed from several knowledge-based attributes and high-level factual instances. Analyzing behavioral data patterns of evaluable usability property between Web and society in spatial-temporal dimensions is the highlight of research, based on which the multidimensional data models are designed. To cover Research Objectives 1 and 2 as cited in Section 3, we rigorously put model design considerations with new design-science features. The DWE architecture uses various social network features, types of technology users, and their significant relationships to model diverse ecosystems.

Description of multiple systems and selection of different schemas for each ecosystem is inevitable, weighting as composite measures in the DWE. Realistically, DWE is an egghead for hundreds of data attributes with volumes of databases and instances in multiple domains and corresponding systems; all can store in a single repository. The spatial-temporal dimensions are added attributes, controlling the modelling process and the schemas connecting geographical ecosystems. For this purpose, we map and model the attribute dimensions using robust modelling methodologies that include data modelling, schema selection, data warehousing and mining, data visualisation and interpretation, encapsulated in an architecture as described in Nimmagadda et al. (2021). For managing complex and ecosystem applications, we have chosen star and snowflake schemas to combine into fact constellation schemas because of the fact, they can accommodate multiple fact tables with necessary ecosystem depictions and constraints (Nimmagadda et al. 2021). However, the digital ecosystem is closely associated with various elements and processes and their chains (conceptualized and contextualized events interpreted in between various entities or dimensions) in spatial-temporal domains where they constantly interact and communicate through digital media (Bar-Yam 2002).

Research Objective 1 emphasizes the integrated framework rigorously put on the network data science of attribute models and their adaptations in the DWE. It is characterized as DWE, in which the digital data are in Big Data scales (Sivarajh et al. 2017). Volumes and varieties (categories) of data sources are typical in such Big Data representation, particularly in DWE contexts. Different attribute dimensions are interpreted in diverse domains of the Web ecosystem. In such contexts, we consider "search engines", "social media", "tech concepts" dimensions and their attributes. In addition to describing an ecosystem, we depict the connectivity between chains, domains, systems, and their attribute dimensions, as a function of sustainable articulations in the DWE (Figure 1). In the current research, we highlight the facts of understanding different sub-systems and systems how they interact in a manner the data are manageable with knowledge of ecosystem scenarios despite varying attributes of social media, tech concepts and tools. The dimensions and fact instances of social network users, usability and popularity rates are acquired from existing data sources (Statista and Data Banks) and Google trends of *Search Engines, Social Media, Tech Concepts, Tech tools* entities to document and model in the DWE repository systems. We have built an integrated metadata model through the workflow, in which a series of artefacts performs several IS tasks (Figure 1). Metadata is all about the description of the data. The data described in each task of IS artefact design, use, development and implementation present within the same framework. The outcome of the research framework is metadata implementation.

5 Analysis and Discussions

Statista.com and Worldindata.org have published secondary data instances. Srivastava (2008) describes data mining procedures for social network analysis. Von Davier et al. (2019) provide detailed insights of the "data cubes". Data cube represents three-dimensional range of values, enabling data modelled and viewed in multiple dimensions. Various data slices are extractable from multidimensional data cubes of the DWE. We analyse the social networks and their data analysis. The knowledge obtained from the metadata of DWE is presented in pictorial form (Figures 2-4). Metadata views generated using the integrated framework are discussed in the following sections. The discussions explain the contribution of the research, substantiating the views provided in Sections 1 and 2.

Various data views extracted from metadata are analysed for meta-knowledge in the DWE contexts. Scalar plot views drawn between different attribute dimensions of DWE indicate strong usability attribute strengths with density and orientation attributes (Figures 2a and 2b). We visualize the connectivity as interpretable through framework articulations and various lines and arrow mark dimensions connected to every rectangular box. Each rectangular box construes an IS artefact. The research focuses on developing digital web ecosystem theory and its implication in resolving societal challenges. They reveal new knowledge of attribute relationships that are inherent in various ecosystem contexts. The line and scalar plot views surface with new visions of relationships between attributes of technology and society. As presented in Figure 2a, the usability of search engines ranges between 60-100 per cent. Popularity sentiments are proportionate to usability property instances. Google usability is analysed for its prominence between the years 2015-16. In comparison, Yahoo usability has gone down by 5-10 % in the same year, but with noticeable usability in 2012. Similar is the case with the “Google Chrome” search engine. Other search engines such as “Bing and Wolfram Alpha” have parabolic trends. Whereas “Baidu and AOL” have shown control in the market around the year 2004, however, their usability has fallen sharply during years 2017-18.

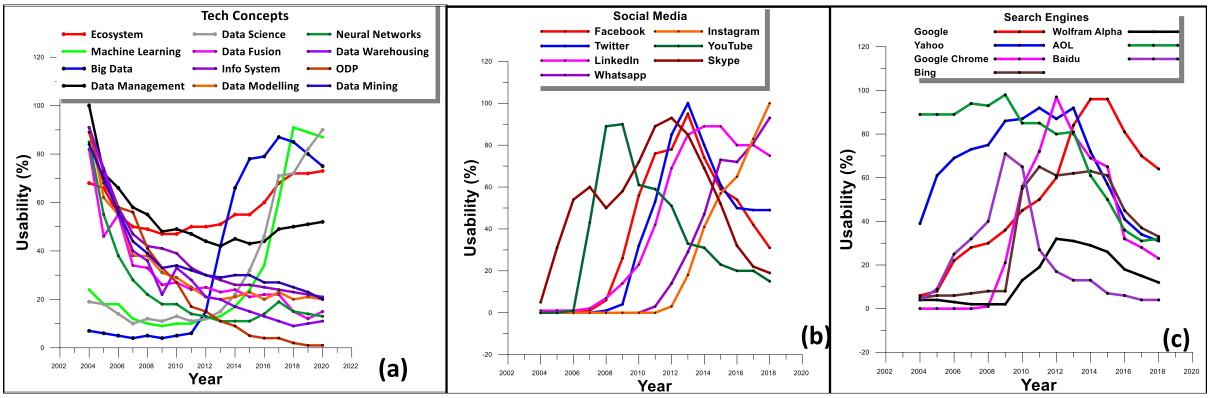

Figure 2: Line scalar plot and data views of (a) search engines, and (b) social media extracted from the DWE framework (Research Objective 2)

We further intend to find the connectivity between search engines and tech tools in the DWE contexts through usability attributes. The regressions and correlation coefficients computed in-between attributes suggest a strong relationship since they exhibit more than 80% correlation except for “Wolfram Alpha” (though not presented here). “Google, Yahoo and AOL” have shown strong popularity associations with more than 90% of correlation (Zhu et al. 2020). The periodic connectivity of usability, attributed from or between search engines, is robust, suggesting search engines are ecologically supportive to mass populations, especially in 2004-2016 years.

The usability attributes of social media exhibit an instance range between 40-100%, as shown in Figure 2b. We demonstrate the associativity between social media through types of curves drawn using the line and scalar plot views. The “Google” trend attributes of social media are analysed concerning their prominence in between years 2006-18, but the usability trends of “Facebook and Twitter” have gone down by 10 % during years ranging 2016-2018. However, they exhibit noticeable popularity during the years 2012-2013. At the same time, the usability of “LinkedIn, WhatsApp, and Instagram” reveal a downward trend, including YouTube. However, the popularity attribute of “Skype” is strong during the years 2010-14. The social network associated with “WhatsApp” is getting stronger in 2018, including the usability trend of “Instagram”. The Correlation Coefficients (CC) computed for these attributes offer a strong relationship since they exhibit more than 80% correlation. In contrast, LinkedIn, YouTube and Skype have much stronger usability attributes with more than 90% correlation, suggesting more societal support. As shown in Figure 2b, the periodic connectivity of usability attributes of social media is strong, inferring most of the social networks are ecologically cordial, connectable to mass populations, particularly in-between years 2006-2018. The broader views of tech concepts are interpreted with a 20-100% usability range, as presented in Figure 2a. The usability of tech concept attributes is analysed for its prominence in different time-periods. Still, the usability of “data management”, “data science”, “ODP”, “Neural Networks” tech concepts have gone down by 10% during the periodic range 2016-2018. However, a discernable usability trend is observed for all these tech concepts during time-periods 2012-2013. At the same time-periods, the popularities of Big Data emerge with upward trends, including ‘machine learning’ and ‘data science’ concepts. However, the usability of machine learning and data science concept attributes is more robust during 2014-18. Broadly, the usability of all tech concepts has exponential regression trends after a fall in 2006 – 2016 years.

Data science and High-Performance Computing (HPC) are added support and guidance to the proposed IS artefact implementations. They are beyond the scope of the current study. However, social network data science are deduced as part of the current scope. The technology associated with 'data fusion' receives stronger attention in 2018, including the popularity of "Big Data", "data science" and "HPC" in the same year. The polynomial regressions are presentable for attributes of the usability of tech concepts at different *year* attributes. The Correlation Coefficients computed for these attributes suggest close relationships between different tech concepts that exhibit more than 80% correlation, compared with usability attributes of tech tools. The periodic connectivity of usability attributes of tech concepts is strong, suggesting most concepts are ecologically durable and connectable to mass populations, particularly in 2004-2018 but with downward trends between 2006-2016 years. The DWE is interpretable with the advantages and disadvantages how the item numbers 8 and 9 of Figure 1 can facilitate the interpretation of the data slices, extractable from DWE metadata. In the following sections, we interpret various data and map views that provide new insights of DWE with improvements and the data science of social networks. Social network models are presentable in different map and bubble plots, including scalar-line plot visualisations. They are presented various scalar line and bubble plot views as shown in Figures 2-4.

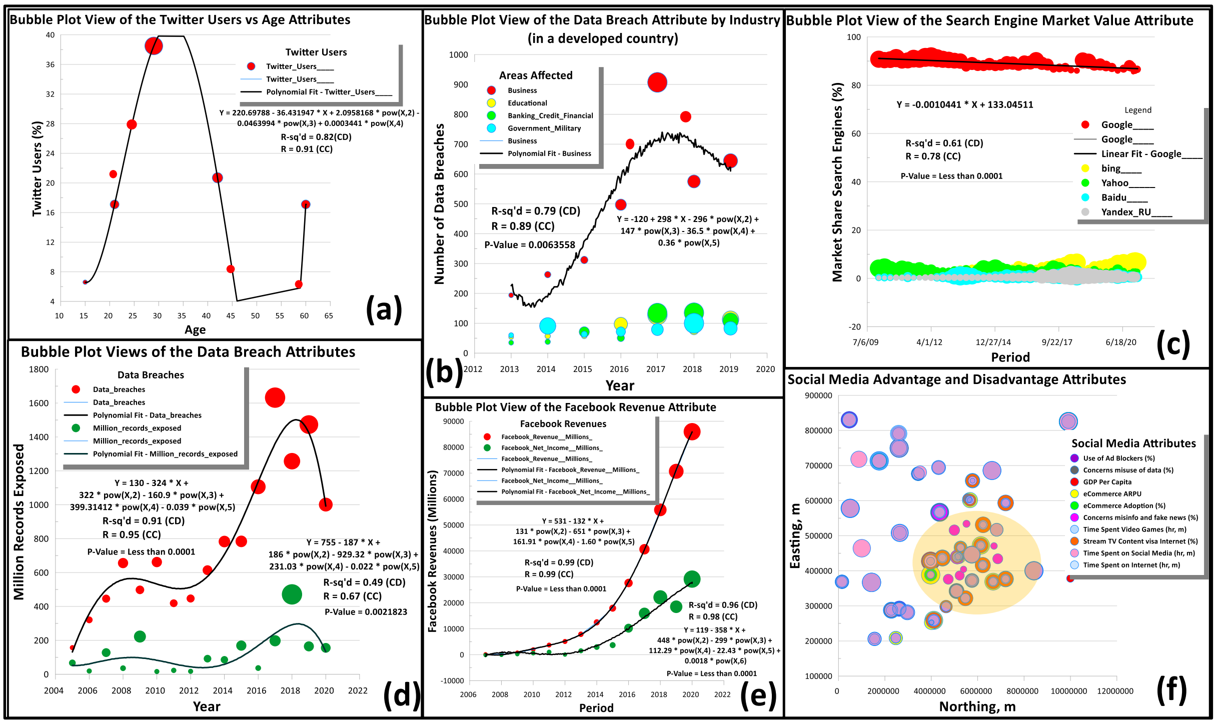

Figure 3: Bubble plot views and their regressions (a) age vs twitter users (%) (b) data breach by industry (c) search engine market value (d)data breaches vs data exposures (e) revenues made by Facebook and (f) social media attributes superimposed (Research Objective 2)

We further examine the data relationships in usability responses observed through the bubble and line-scatter plot views interpreted for social networks. Interesting trends discerned from social networks and other tech concepts show sustainable relationships between the Web and society, as demonstrated in Figures 3a-3f. Densely clustered big-size bubbles suggest that prominent social networks are closely connected to popular technology networks. The outcome of the framework, described in Figure 1, is presented in interpretable data views that provide new insights into social network data science. The authors presented an album of the attribute descriptions (Figure 3) that comprise tech users, IS artefact usability, data breaches from social networks, the market value of search engines, revenues made from social networks attributes. Figure 3a, Twitter users and their age groups. 20-45 years, the aged group has dominated Twitter use. Figure 3b describes the data breaches in different industries; the business sector suffered the most compared with other industry sectors. In Figure 3c, the market value of search engines is demonstrated in which periodic value of Google has been predominant compared with other search engines. In Figure 3d, the problem of data breaches is serious, around 80% compared with data exposures that amount to 20%. The revenues made from Facebook are huge, and the periodic increase is exponential, as shown in Figure 3e. In Figure 3f, a bubble plot is presented in spatial visualisation, superimposing several social network attributes.

Maps are presented to investigate and interpret the attribute trends that can show direction, true distances in northing and easting coordinates, areas of attribute interests, and various shapes. Map visual analytics can provide network usability activity, which can segregate intense attribute areas. Several maps views are presented in different spatial coordinates in Figures 4a- 4f. Several lobes are interpreted in the maps views, computed for social network attributes. For example, spatially varying internet usability, personal data misuse, misinformation and fake news, e-commerce adoption and mobile e-Commerce adoption are analysed. The attribute strengths are shown with yellow coloured envelopes with areas of strong social network activity compared with weak attribute instances in other areas, shown in green coloured network space. Lobe 1, lobe 2 and lobe 3 appear to have common social common attribute occurrences, implying that these attributes are connectable.

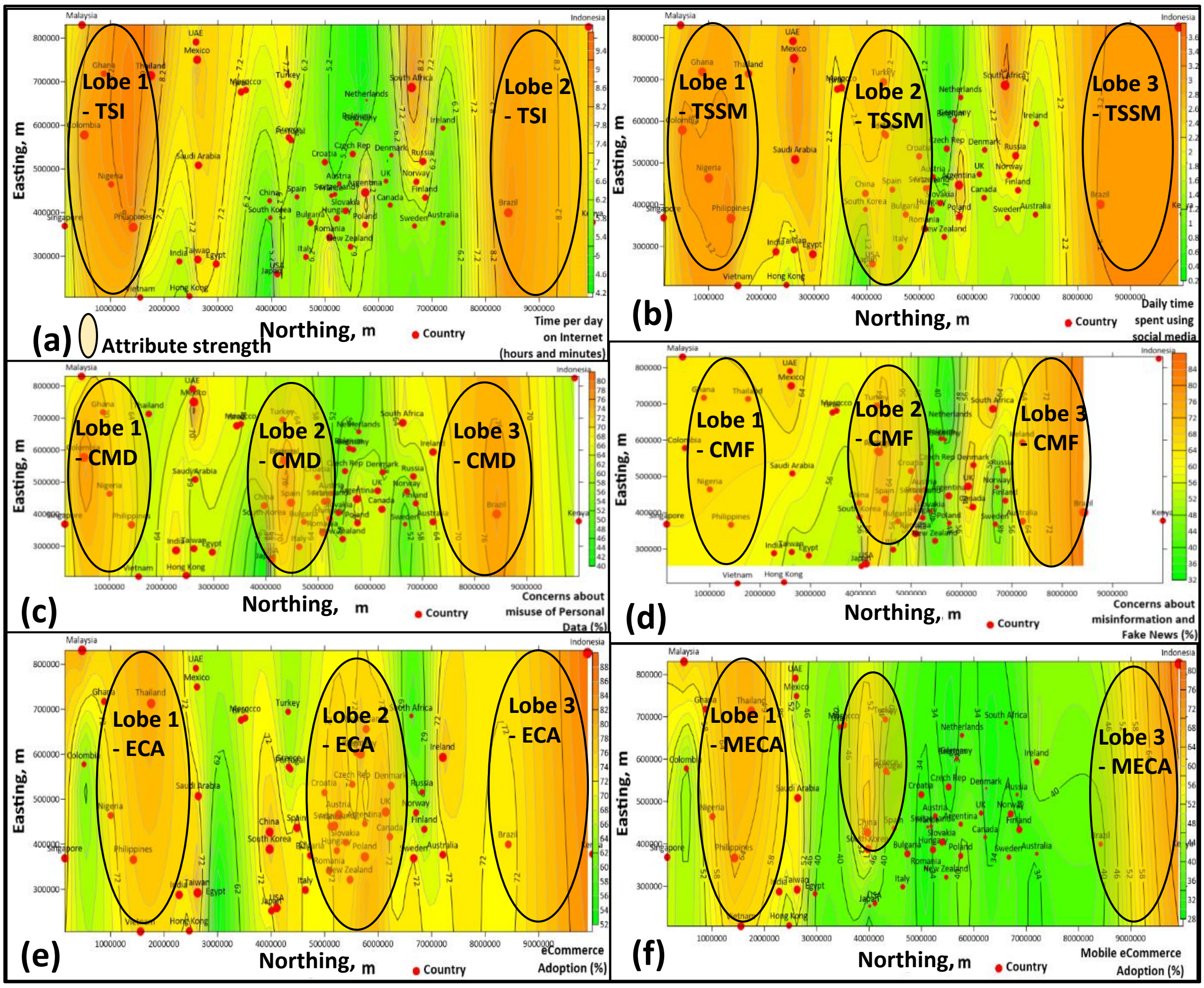

Figure 4: Map views of tech users with spatial usability visualisations (a), (b), (c), (d), (e) and (f) (Research Objective 2)

In addition, as described in Bello-Orgaz et al. (2016), information fusion appears to have a role in integrating concepts, tools and connecting them among geographically populated masses as social Big Data. The dissemination of knowledge of social media among the mass population is interpreted as a conceptualized attribute that motivated us to assess the associativity between tech users. More than 40-50 per cent of the population appears to have a prominent role played with Internet penetration among masses, as shown in Figures 2-4. Internet use among different countries is shown in Figure 4 in several lobes (envelopes), inferring 40-100 % of usage.

6 Significance and contribution

Dissemination of information has implication in the current digital ecosystem contexts and its dependence on its fusion (Bello-Orgaz et al. 2016; Rogova and Bosse 2010). Social media and Big Data need to leverage various data mining tools, machine learning, computational intelligence, the semantic web, and social networks to eliminate any ambiguities arising during the interpretation of internet usability and social network usability and popularity sentiments. The integrated framework brings together various artefacts to unify social network science interpreted with usability and their interactions. We have used polynomials to build relationships between technology, social media and the population range. The contribution of the research lies in adhering to and envisaging the relationships between technology and societal impacts. Polynomials provide a broad range of approximations throughout the curvature, in addition to resolving associativity between dependent and independent variables. The contribution of the research lies with the facts and interpretative insights of relationships between technology and society that can improve the digital transformation with interlinked business growth, market values, and people perpetuations, resolving the complexity of knowledge-based information solutions.

7 Conclusions and future vision

We interpret resilient and sustainable associativity between social networks, technology tools and societal challenges. The DWE has emerged with multiple domains and systems, easing the complexity through ecosystem theory and its development while managing social network informatics and science. The data management and documentation facilitate the integration process in the DWE theory. In addition, the Big Data characteristics and their anomalous are added features to resolve issues associated with large-scale ecosystems in DWE contexts. The IS artefacts, represented in different data schemas, are based on conceptualization and contextualization features, simplifying the DWE architecture. The architecture successfully makes logical connections between social networks through attribute relationships. The attribute connectivity mapped in the metadata depends on the quality of data views presentable in new knowledge domains. The usability and network popularity sentiment attributes are used to interpret the entities and dimensions of the DWE. DWE framework architecture generates metadata within a multidimensional repository. The repositories are explored to exploit the usability of the internet for society and user concerns. The data views describe popular sentiments of the DWE in spatial-temporal dimensions. The regressions computed between diverse attributes of technology-society provide new insights of DWE with interpretable relationships, including their predictive models.

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