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Enterprise Personal Analytics:
Research Perspectives and Concerns

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ABSTRACT

Modern enterprise technological landscapes are being impacted by the increasing individuation of information systems (IS). Consequently, the end-user computing phenomenon is being extended to incorporate a multitude of nascent possibilities for organizations. One promising avenue encompasses the use of business analytics. Common categories of enterprise intelligence analytics are traditionally derived from activity patterns and collaborative routines. The scope of this article focuses on another emergent category of analytics which is referred to as "enterprise personal analytics". This topic has been only minimally analysed in IS and business intelligence research. This article therefore extends understanding by presenting a grid framework which comprises various combinations of research stakeholder perspectives and concerns. This framework can be used to guide and coalesce future research on illuminating how personal analytics can be used effectively in an enterprise setting.

KEYWORDS

Business Analytics, Business Intelligence, Enterprise Personal Analytics, Information Systems Individuation, Research Framework

1. INTRODUCTION

Evolution is happening when you are not watching. (Baskerville, 2011)

As our lives "…become immersed by powerful digital devices and services, questions of implications for individuals' lives as well as their social interactions and structures arise… this emerging fully digitized and connected environment implies changes to the development, exploitation and management of personal information and technology systems…" (Matt et al., 2017). One promising technological trend in this regard will be the use of personal analytics which first appeared in the innovation trigger category in the Gartner hype cycle for technologies in 2016. According to Ingelbrecht and Herschel (2015) "personal analytics empowers individuals to analyse and exploit their own data to achieve a range of objectives and benefits across their work and personal lives". Personal data can relate to biometrics, personal finance, social media activities, health status, behaviours, emotional states, mobility, interest areas and so on. In an increasingly data driven society, the emergence of personal analytics has been catalysed by the convergence of mobile (new and emerging ambient user experiences), cloud computing, business intelligence and social technological advancements.

Organizational interest with regards to enterprise personal analytics is also beginning to gain traction. Extant evidence highlights how "top-performing organizations use analytics five times more than lower performers" (Lavelle et al., 2011). Personal analytics can empower individuals within organizations to manage their digital working lives from descriptive, diagnostic, predictive and prescriptive points of view. While traditional organizational "intelligence metrics deliver a big picture of structures, processes, and roles, more detailed and personified analytics provide individuals with a mirror view of their actual versus desired way of work and the resulting personal productivity" (Dobrinevski, 2013). This personal analytics phenomenon has been catalysed by a multifaceted and amorphous concept known as information technology (IT) consumerization in conjunction with a number of personal learning analytics trends (See Section 3). IT consumerization in its broadest sense refers to the "phenomenon of more and more employees bringing their own IT into the work place and using these tools for work purposes" (Harris, Ives and Junglas, 2012). This "consumerizing of the previously sovereign territory of the IT department" has led to a multitude of benefits in terms of innovation, employee satisfaction and productivity (See Harris, Ives and Junglas, 2012). In order to leverage these benefits enterprises are responding to IT consumerization by introducing a number of proactive strategies. For example, in an effort to reduce employee medical insurance costs, organizations are providing their staff with Fitbit health technology wristbands in an effort to promote corporate wellness and motivate healthier employee lifestyle behaviours. Health insurance providers such as Unitedhealthcare currently offer this service for their organizational clients. This employee data is analysed by a third-party company called Qualcomm Life. Based on how active the employees are, as measured by the Fitbit, they can receive as much as $1500 towards their health care services. Similarly, enterprises are using employee's personal analytics in order to enhance operational efficiency, strengthen employee retention and relationships, enhance decision making and provide actionable reports. Companies such as DATIS provide a cloud based talent management software solution which provide managers with dashboards which enable them to analyse employee data such as timesheet submissions, pending workflow requests, corrective actions and so on.

While enterprises want the benefits of IT consumerization and personal analytics, they also recognise the unique risks which are inherent to these developments. Much research pertaining to personal analytics is fragmented and presented solely from the perspective of the enterprise (e.g. tracking of employee metrics) or the individual (e.g. use of personal data to improve personal lives). In lieu of the significant role information and communication technology (e.g. databases, spreadsheets, decision support systems, data visualisation tools, cloud based software, mobile etc.) continues to play in enabling organizational personnel to effectively to carry out their routine tasks, very little information systems (IS) and business intelligence research exists on how on enterprises and their workers can simultaneously and harmoniously leverage the benefits of enterprise personal analytics data. This is understandable given the embryonic nature of the personal analytics concept, specifically in the context of an enterprise setting. Additionally, it has been claimed that the IS discipline have largely benighted the individuation of IS (See Baskerville, 2011) and the digitisation of the individual concepts. Moreover, there is an increasing reluctance of enterprises and individuals to use personal analytics technologies due to trust, surveillance, security, and privacy literacy concerns. This is best highlighted in the wearable technology fitness industry where privacy concerns are hampering the beneficial impact of applications such as Fitbit, Jawbone, Fuelband, and Nike+. This is exacerbated by wearable technology fitness providers who tend to (ab)use opaque, lengthy privacy policies and engage in excessive sharing of data with a multitude of third parties, some of whom are not listed in the privacy policy (Privacy Rights ClearingHouse, 2013). However, there is significant potential, from both organizational and individual worker perspectives, for the use of enterprise personal analytics, but much research is needed in order for the concept to realise its full potential. While several authors have proposed research frameworks for enterprise personal analytics (Kim et al., 2010; Dobrinevski, 2013; Huang et al., 2015), these are not specifically IS or business intelligence focused, but rather provide guidance on individual activity patterns, personal visualization, personal visual analytics and metrics. While such frameworks are useful for specific contexts, there is a need for a dedicated framework to systematically study this topic. Thus, following a comprehensive survey of the literature, we have derived a research framework which can be used to guide future empirical investigation.

This paper is structured as follows. Section 2 describes the literature review methodology, Section 3 provides an overview of specific analytical developments which have shaped the personal analytics landscape, Section 4 provides an overview of our research framework, and Section 5 outlines how this framework can be applied. Finally, we conclude this paper in Section 6.

2. RESEARCH METHODOLOGY

Our objective is to portray enterprise personal analytics as an emerging research area and provide a snapshot to guide future research and development. Thus, we conducted a comprehensive survey of the literature in order to produce a systematic deductive analysis of the concept of enterprise personal analytics (Heyvaert, et al., 2013). An effective literature review not only makes a significant contribution to cumulative culture but also "creates a firm foundation for advancing knowledge. It closes areas where a plethora of research exists, and uncovers areas where research is needed" (Webster and Watson, 2002). The first step in our analysis of the literature encompassed the sourcing of relevant research resources via scholarly databases and manual searches. To ensure the consistency and reliability of the search process we used a three stage literature mapping protocol as prescribed by Kitchenham and Brereton (2013) to search, select, appraise and validate the extant. For the initial *stage 1*, we conducted a rigorous search of the academic literature was undertaken in all subject areas across all years (until 1 February 2017) using seven prominent databases to produce a research resource set which was representative of the current status of enterprise personal analytics research: EBSCOhost, JSTOR, ProQuest, Google Scholar, PubMed, Scopus, and Web of Knowledge (Table 1).

Table 1. Databases accessed, query method, and search results

Database	Query (If Modified by Search Engine)	Source Types (If Available)	Research Resource Total
EBSCOhost		Books, Academic Journals, Reports, Conference Materials, Articles,	65
JSTOR	((personal analytics) OR ("personal analytics")) AND ((cty:(journal) AND ty:(fla OR edi OR nws OR mis)) OR cty:(book))	Books, Miscellaneous	10
ProQuest			277
Google Scholar			243
PubMed			12
Scopus	ALL (personal analytics OR "personal analytics") AND (LIMIT-TO(DOCTYPE, "cp") OR LIMIT-TO(DOCTYPE, "ar") OR (LIMIT-TO(DOCTYPE, "IP"))	Scholarly Journal, Dissertations and Theses, Conference Papers and Proceedings, Reports, Working Papers	45
Web of Knowledge	Topic = (personal analytics) OR Topic=("personal analytics")		54
All Databases			706

This selection of databases was informed by the multidisciplinary nature of personal analytics research. The term 'enterprise personal analytics' is novel and not established as a subject or thesaurus term; thus, the phrase 'personal analytics' was used as a keyword to determine how papers were filtered, and criteria were established to ensure that the papers included for review met the definition established in this paper. To support the manual search, an automated search based on citation analysis (also referred to as snowballing) was performed. Relevant research sources identified from full research papers were also collated. Next, the researcher applied an identical search and select protocol for the IS literature domain. All 706 research resources were imported directly into an EndNote database. Using EndNote's 'find duplication' feature seventy duplicates were removed. The remaining 628 research sources were further filtered using stage 2 and stage 3 of the mapping protocol. Stage 2 selection processes encompassed a decision making process to include or exclude relevant research papers from the data extraction process. The "final decision took place when the research sources were read in parallel with data extraction and quality assessment. Stage 3 search and selection took place in parallel with data and quality extraction from the research sources identified in stages 1 and 2 and comprised three main tasks: search process validation, backward snowballing and researcher consultation" (Kitchenham and Brereton, 2013).

With a strong focus on the use of personal analytics within an enterprise setting, stages 2 and 3 resulted in the removal of: irrelevant research articles (e.g. analytical chemistry, astrophysics, mathematics etc.), further duplicates not picked up by EndNote (e.g. surnames and first names misplaced), materials no longer accessible, questionable sources (e.g. credibility of resource could not be verified) and research sources where personal analytics was only briefly mentioned and not the main theme of the content. In total 563 articles were discarded which resulted in a final total of 56 research resources remaining in the EndNote database for further analysis. We used NVivo 10 software as a means of systematically classifying and revealing academic insights on enterprise personal analytics. While we did not undertake a grounded theory approach, following Ritchie et al. (2003), we used a multistage hierarchical data analysis approach comprising four analytical cycles which incorporated open and axial coding techniques based on the recommendations of Strauss and Corbin (1998). The hierarchical data analysis procedure used was an iterative process whereby as "categories are refined, dimensions clarified, and explanations are developed, there is a constant need to revisit the original or synthesized data to search for new clues, to check assumptions or to identify underlying factors" (Ritchie et al., 2003). The primary analytical cycle comprised a process of open coding which was used to identify codes from the research resource title, keywords, abstract and content. As the analysis advanced, the codes and concepts became more conclusive and definitive. In this process, fifteen to twenty codes were identified.

In the secondary analytical cycle, axial coding was used to reassemble the data that were fractured during the open coding phase by identifying causal conditions and relationships between the concepts and categories (Strauss and Corbin 1998). The coding process continued until the categories were deemed to be theoretically saturated (Strauss and Corbin, 1998). The tertiary analytical cycle encompassed a process of triangulation and peer debriefing. In order to confirm representativeness, once the coding was completed, the resulting coded headings were juxtaposed and triangulated in order elucidate similarities and differences. Peer debriefing enabled us to use external groups as a "sound board for further validating the final set of themes which emerged from our analysis (Schwandt, et al., 2007). Consequently, the 56 research resources were full text reviewed and coded to create a research framework as shown in Figure 2. Prior to presenting this research framework, we provide an overview of the significant developments which have shaped the personal analytics landscape.

3. NAVIGATING THE PERSONAL ANALYTICS LANDSCAPE

Personal analytics is a multidisciplinary concept spanning a breadth of disciplines. Empirical studies across these disciplines have begun to explore how personal analytics can be used in certain contexts (e.g. using personal analytics technologies to transform an individual's behaviour towards desired outcomes). We discuss these in turn.

3.1. Learning Analytics

Learning analytics refers to the "measurement, collection, and analysis of reporting data about the progress of learners and the context in which the learning takes place" (Sclater and Mulan, 2017). The global learning analytics market is forecast to reach $2.44 million by 2019 (Infiniti, 2015). The concept of learning analytics can be traced back to the early 90s where the analysis of market trends using browser and web log tags began to gain prominence (Educause, 2010). The emergence of big data, personalised learning online learning and student digital footprints saw learning analytics being increasingly used to measure, compare and improve the performance of individuals with regards to achieving better activity outcomes (Norris et al., 2009). Academic analytics tools such as virtual learning management systems were rapidly adopted by academic institutions on global scale in order to improve the effectiveness of institutional learning and teaching (Fournier, Kop and Sitlia, 2011). There is evidence (See Sclater and Mulan, 2017) to suggest that these virtual learning management systems can not only enhance student learning, but can also modify their behaviours towards desired academic educational outcomes (e.g. grade improvement, independent learning, critical thinking, etc.). Moreover, extant research suggests that learning analytics can be used to design interventions (e.g. early warning systems) for identifying at risk students (Howard, Meehan and Parnell, 2016). Learning analytics tools are also being used by non-academic institutions to measure employee engagement. D2L and SAP SuccessFactors are examples of enterprise cloud based virtual learning management software which enables organizations to operationalise learning activities and accompanying metrics for coaching/mentoring, professional skill and leadership development, personalised learning experiences, ubiquitous and immersive learning, social learning and providing learning as a human resource benefit. The ultimate objective of these types of enterprise learning management systems is to pinpoint training needs, support employee development, improve business outcomes, maintain workforce engagement and sustain employee retention (Mattox & Buren, 2016).

3.2. The Quantified Self

The quantified self, also known as lifelogging or auto-analytics, refers to the increasing use of technology to collect and analyse data pertaining to varying aspects of one's life such as performance (e.g. mental or physical), inputs (e.g. calories, air quality) and physiological states (blood sugar levels, mood, arousal). The quantified self-movement aligns itself with similar concepts which have been proposed by philosophers such as Michael Foucault who highlighted the importance of self-reflection and the use of self-knowledge for personal development (Melanie, 2013). Due to the commercial availability of sensors, "data describing our health and fitness (e.g., exercise logs, pedometer data) and even our resource usage (e.g., utilities such as water, electricity use) are easily available to us and enable us to explore information about ourselves, our communities, and issues that are personally relevant and important to us" (Huang et al., 2015). For instance, the use of mobile health (mHealth) and wearable health applications for incentivizing health behaviour change continues to grow at an unprecedented rate. This growth has been accelerated by recent advancements in 'smart' mobile technology such as cloud computing, internet of things, sensors, phones, tablets, wristbands and watches. Physicians and other health care professionals are increasingly advising their patients on the merits of using these applications as health monitoring (e.g. diabetes, heart rate etc.) and health improvement tools (e.g. smoking cessation, weight control etc.). mHealth fitness applications such as Fitbit, Jawbone, Fuelband, and Nike+ have become increasingly popular with an estimated 25 million fitness applications sold in 2015 (GFK, 2015). A wearable camera company called Narrative have created a smart camera which is powered by machine learning, takes photos every 30 seconds, interprets and tags emotions for facial expressions. This smart device enables children with autism to improve their capability to recognise other people's emotions (Gillam et al., 2015).

3.3. Human-Centric Personal Analytics

According to Lee and Balan (2014) advances in mobile computing "has allowed unprecedented access to deep and enriched human contextual information, for example, mobility, activity, and interactions. This access is possible through smartphones that generate rich data sources, including application usage (e.g., social network postings, search history, and call records) and physical sensing data (e.g., location, activity)". Current research human-centric methodologies encompass the investigation of two unique characteristics. While the first characteristic "focuses on high-level human-centric contexts (e.g. intention, engagement, emotion, attention, fatigue, anxiety, depression, distractibility, mindfulness, etc.), the second characteristics focuses on flexible combinations of real-time and historical data which can be queried for deeper insights" (Lee and Balan, 2014). Examples of human-centric personal applications include BeWell, Walksafe, EmotionSense, MoodScope, and StressSense. In the case of StressSense, an application which can detect a user's stress levels by using a smartphone's microphone to analyse vocal stress, preliminary evidence suggests that the application is 81% accurate when used indoors and 76% accurate when used outdoors (Jaffe, 2012). It is envisaged that these human-centric applications will be used by organizations in the future to create smart working environments (e.g. workstations) for their employees which can change automatically based on individual worker data. For instance, imagine a scenario where a stress sensor alerts an employee via a desktop computer pop up message to the fact that they are reaching their safe stress threshold. In line with company policy for this specific event, the employee may disengage from the stress producing event and engage in stress relieving activities (e.g. mindfulness techniques, a walk, etc.).

3.4. Sports Analytics

There is strong evidence from the literature regarding the successful transference of sporting concepts (e.g. peer coaching, metrics, sigma lean belts and so on) to business environments (See Davenport 2014, Liu et al., 1998, Soane, 2014). According to Liu et al., (1998) "many organizations are now using sporting analogies and training methods, to enhance the performance and ability of their employees for greater efficiency, productivity, and company profits". The reasoning for this is that the sports industry is one of the most scrutinised in the world, whereby the use of "analytics to measure team and individual performance in the sports world has much to teach managers about alignment, performance improvement and business ecosystems" (Davenport, 2014). There are also commonalities between sports teams and business team contexts. For example, both environments can be characterised by a similar ethos of competitiveness, incentives, individualism, camaraderie and achievement (Peters, 1996, Dovey and Singhota, 2005, Soane, 2014). Modern enterprises are inundated with a never-ending stream of data, technologies and analytics to exploit. Subsequently, there is emerging research which states that enterprises can successfully transfer the concept of sporting analytics techniques into their own workplaces. Davenport (2014) cites Procter and Gamble (P&G) as an exemplar who have done just that. P&G use sophisticated sporting analytics techniques in order to focus on the human dimension in order to enhance individual and team performances such as: evaluating across different enterprise team compositions for various customers to identify their star employees/players (e.g. +/- players); co-developed business sphere rooms for reviewing and acting on team and individual data analyses; embedded analysts in close proximity to CEOs (e.g. placed on the bench with the coach) and most significantly employees keep track of and analyse their own performance metrics in order improve on them.

3.5. Gamification

The gamification concept is rapidly growing in popularity among practitioners, business professionals and academics alike. Leveraging game design elements, gamification is currently being used in non-game contexts to enhance products and services in order to intrinsically motivate customers toward preferred behaviours, enhance end-users' experiences and increase employees' incentivization and engagement (Deterding et al. 2011; Blohm and Leimeister, 2013; Seaborn and Fels, 2015). A 'Gamification 2020' report highlights how gamification, combined with other emerging trends and technologies, will have a significant impact on: innovation, the design of employee performance, the emergence of customer engagement platforms and the gamification of personal development (Gartner, 2014). From an academic perspective, gamification has also received increasing attention in recent years (Huotari and Hamari, 2012; Thiebes et al. 2014; Seaborn and Fels, 2015). This is underlined by gamification's popularity across academic outlets in terms of journal special issues, conference tracks, special interest groups, workshops, panels and so on. Additionally, the appearance of the terms 'gamification' and 'game elements' as methods with which to motivate and engage end-users are fast increasing in popularity with regards to academic inquiry (Thiebes et al. 2014; Hamari et al., 2014). Gamification is currently being used for self-tracking and self-surveillance purposes and aligns itself well to personal analytics applications. For instance, gamification techniques are being incorporated by companies such as Nike, FitBit and Under Armour into their health and fitness products and mobile applications.

3.6. Personal Cloud

The emergence of cloud based-digital technologies has presented many organizations with the scope to reinvent how they conduct business (Choudary and Vithayathil, 2013; Demirkan et al. 2014; Clohessy, Acton and Morgan, 2017). Further, as a disruptive and a transformative technology, "cloud services affect every aspect of our lives, be it working, shopping, or watching movies" (Benlian et al. 2016). Investments in cloud-based digital technologies continue to rise as evidenced by a recent survey conducted by the society for information management (SIM) which highlighted how cloud computing constituted one of the top five IT investments made by organizations in 2015 (Kappelman et al. 2015). The personal cloud is the "collection of content, services and tools that users assemble to fulfil their personal digital lifestyle needs across any device. Each user's personal cloud is unique and evolving, as the user's daily needs change and as vendors and products come and go...Looking forward, we see continued upheaval and challenges from the blending of personal and corporate digital tools and information within each user's life" (Kleynhans, 2015). This new concept has been shaped by two technological trends: increased intelligence capabilities pertaining to the end user experience and increased access to personal information. For instance, Google have incorporated sophisticated recognition algorithms to their apple iCloud photo application which automatically tags locations, people and events for personal photos taken on a mobile device. Future personal cloud developments are expected to centre on four areas: virtual personal assistants, IoT, wearable and secure authentication technologies.

4. RESEARCH FRAMEWORK

The use of personal analytics in an enterprise setting is different from other contexts (e.g. private use). This has implications for which aspects of personal analytics should be researched in an enterprise setting context. Based on our comprehensive survey of the literature (Section 2) we identified five specific concerns pertaining to the use of personal analytics in an enterprise setting which we discuss in section 4.1. These concerns are depicted as one dimension of our research framework. As enterprise personal analytics involves a number of stakeholders it is useful to study the concept from different perspectives. Our analysis revealed several perspectives namely that of companies, workers and the modality representing the mode through which companies enable workers to use personal analytics. These perspectives are further outlined in section 4.2. Consequently, the research framework depicted in Figure 2 defines a two-dimensional grid (stakeholder perspectives and concerns) which can be used to guide and bound future research in the area of enterprise personal analytics.

4.1. Concerns

4.1.1. Individual Information Systems Architecture

Advances in information and communication technologies over the last 20 years has "enabled more-and-more complex individual IS" (Baskerville, 2013). However, this individuation of IS has largely gone "unnoticed in the IS research discipline, simply because we have traditionally defined the field in terms of social, organizational, and managerial relations" (Baskerville, 2011). According to Harris, Ives and Junglas, (2012) "IT consumerization, or the adoption of consumer devices and applications in the workforce, is pervasive. Employees bring computer tablets and smartphones into the workplace and harness social media applications and special purpose apps for their work lives". Figure 1 depicts a typical individual's information system architecture. The vertical arrows represent two work systems. The first is the individual's work system as an employee and the other is the individual's personal work system. These systems are facilitated by cloud computing technologies which produce and consume services. Baskerville (2011) opines that the IS discipline can no longer ignore this phenomena for the following reasons. First, individual IS represent the most recent frontier for the computer IS design. Second, they are complicated and unique systems which cross boundaries between personal life (e.g. social aspects) and work life (e.g. organizational aspects). Third, these systems merely just store data, individuals are "actively collecting data and processing it into information for various purposes and feeding it outward" (Baskerville, 2011). The dearth of business intelligence research into the individuation of IS leads to a number of possible enterprise personal analytics architecture research questions (see Table 2).

4.1.2. Knowledge and Intellectual Property (IP)

The main goal of any business analytics initiative is knowledge discovery (Piatetsky-Shapiro, 2007; Chen et al. 2012). Business analytics involves "acquiring new knowledge through an analysis of data and information in its information assets, and employing knowledge to develop and implement

Figure 1. A typical individual's information systems architecture (Baskerville 2011)

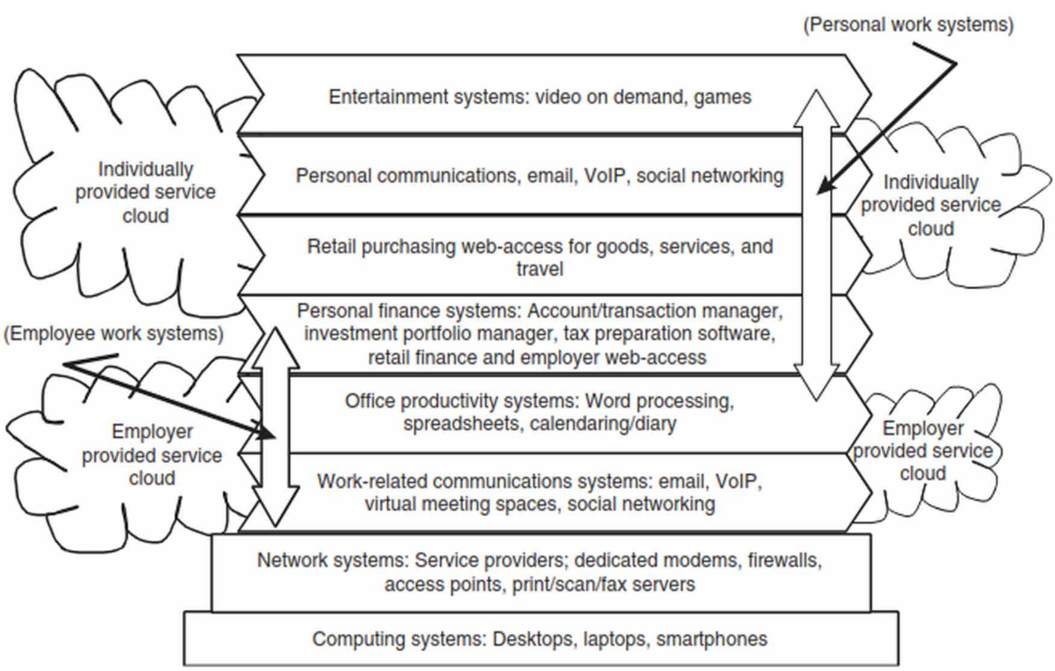


Figure 2. (I) A multi-concern, single perspective study; (II) A single-concern, multi perspective study; (III) A single-concern, single perspective study

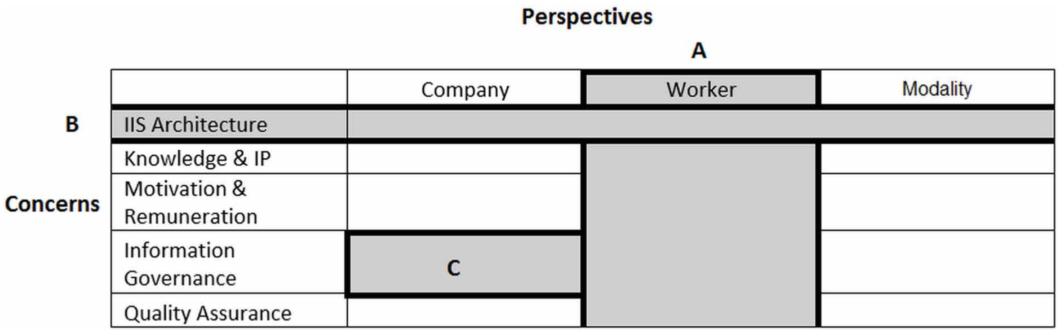


Table 2. Research framework to study enterprise personal analytics and example questions

Concern	Company	Worker	Modality
IIS Architecture	What reference architectures are suitable for creating productive and interoperable IIS architectures for workers?	How to effectively develop a flexible IIS architecture which continuously facilitates worker learning and improvement?	How can IIS architectures contribute to the teams' and company's overall goals?
Knowledge & IP	What policies can be put in place for scenarios where workers request access to their personal analytics data when they leave the company?	How can knowledge be created and analysed in a meaningful way by workers?	What digital tools should be in place for effective knowledge sharing between workers?
Motivation & Remuneration	What practices should be put in place to effectively empower and satisfy workers?	How can personal analytics be made appropriate for use in enterprise contexts - including for people who have little experience with data, visualization, or statistical reasoning?	What are the effects of using multiple digital devices and ubiquitous connectivity on individuals' attitudes, behaviours and performance?
Information Governance	How to minimise privacy and IT-security issues for individual workers private lives?	Who assumes the responsibility for `monitoring and controlling worker personal analytics data?	What digital device policies are appropriate for data retention, data sharing and inter team data transfers.
Quality Assurance	Who or what algorithms govern the analysis and presentation of personal analytics data?	What specific individual worker metrics can contribute in a meaningful way?	What digital tools can workers use to ensure the effective sourcing and subsequent analysis of their personal data?

value-creating competitive actions" (Sharma et al., 2010). According to Ruckenstein (2014) "personal analytics is firmly rooted in the externalization of 'nature' as something that people are able to transform. It is not enough to have a more transparent view of oneself, one needs to respond to that knowledge and raise one's goals. With the aid of digital technology, the tracking and monitoring of the self, optimization becomes not only possible, but also desirable". In an enterprise personal analytics context, where the individual worker personal analytics' data is seen as an information asset, the manner with which knowledge and intellectual property is managed becomes of paramount importance. For instance, when an employee leaves a particular company, questions arise pertaining to: who owns the individual workers' personal analytics data? The company or the worker? If the answer to the latter, can the worker use their own personal analytics data as a means of highlighting their expertise and skills to prospective employers (e.g. a form of digital passport)? Moreover, does this transfer of worker personal analytics data make companies more vulnerable to competitors employing collective intelligence (e.g. using competitor data sources to predict their strategies) techniques? Further research is required to determine how companies can effectively implement a requisite level of knowledge production versus knowledge protection in an enterprise personal analytics context. The theoretical justification for this choice has been received empirical support "as a strategic reaction to competitive conditions mandating aggressive use of business analytics for knowledge development juxtaposed with substantial investment in knowledge protection (Liebowitz 2016).

4.1.3. Motivation and Remuneration

The ultimate goal for an organization when designing or introducing a new digital technology or information system is to ensure that people will want to use it (Markus and Keil, 1994). Motivation and remuneration are topics which have received significant attention in the personal analytics literature (Lupton, 2014; Ledger and McCaffrey, 2014; Clawson et al., 2015). How an organization "measures and rewards employee performance matters …aligning incentives with desired behaviours in the context of personal analytics use is important" (Mazzei, 2017). For instance, "most traditional visualization applications focus on supporting expert analysts with respect to their occupational roles. In a personal analytics context, "employees may look into their data with different goals, backgrounds, and expectations (e.g., internal context). However, the vast majority of people are not visualization or data analytics experts, so analytic tools will need to be accessible" (Huang et al., 2015). Social influence and trust may also have negative impacts on workers behaviours (e.g. sharing information, or comparing individual performance with peers). Furthermore, meaningful individual analysis can only be achieved after an adequate volume of data has been collected. The medium through which organizations enable their workers to collect and analyse their personal analytics data will a significant role to play. Research has identified mobile devices and wearable technologies as major instruments which will facilitate an enhanced user experience (e.g. usefulness) in conjunction with a substantial automation of personal analytics (Ingelbrecht and Herschel 2015; Mazzei, 2017). There is also a 'grey area' pertaining to how continuous self-monitoring of one personal analytics can impact workers health. For instance, "it is conceivable that people may become over-reliant on automated systems that provide a false sense of security and they could also suffer from negative consequences of excessive self-monitoring by finding it uncomfortable, intrusive, and unpleasant" (Piwek et al., 2016). Ultimately, organizations must develop enterprise personal analytics strategies that inspire long-term use amongst workers. The lessons learned from the large-scale abandonment of personal health tracking technologies which is currently occurring amongst users (See Clawson et al., 2015) can provide valuable insights.

4.1.4. Information Governance

Information governance is defined as "a subset of corporate governance and includes key concepts from records management, content management, IT and data governance, information security, data privacy, risk management, litigation readiness, regulatory compliance, long- term digital preservation and even business intelligence" (Smallwood, 2014). Ultimately, information governance is concerned with control and compliance with regards the totality of information. Information governance has emerged as a major challenge for organizations in today's environment of big data, business analytics, increasing information risks etc. In the case of enterprise personal analytics this stumbling block maybe more exacerbated. The potential nexus of parties (e.g. partners, workers, customers, data pools, cloud and network providers) encompassed in an enterprise analytics context necessitates robust information governance mechanisms. For example, the privacy and security of personal data generated by workers pose serious challenges. We highlighted earlier how some companies are giving their workers access to wearable technologies in order to reduce health insurance premiums. However, these workers do not own their data. Instead, “data may be collected and stored by the manufacturer who sells the device. Being provided with only a summary of results extracted from these data creates a rather odd paradox for the user - they own the device, but not the resulting data” (Piwek, 2016). Consequently, Table 2 highlights a number of possible research questions in this regard. Lavelle et al., (2011) argues that business analytics mature organizations derive value by effectively embedding information governance policies, toolkits and practices which “align business needs to growth in analytics sophistication”. This leads to a number of promising research avenues which focus on specific contexts such as the manner with which information governance structures evolve as a result of increasing penetration of enterprise personal analytics and the identification of specific governance structures which are more effective in capturing value from enterprise personal analytics-supported decision making. Additionally, there may be a need to develop simple regulatory frameworks which support the validation of enterprise personal analytics initiatives. We envisage that such frameworks could possibly persuade an enterprise to collaborate within a community of organizations who have a vested interest in providing open access to their collective personal analytics methodologies, data collection and analysis protocols. Similar approaches have already been effectively adopted in the wearable technology industry to ensure reliability of the devices in conjunction with alleviating security and privacy concerns (Piwek, 2016).

4.1.5. Quality Assurance

Personal data is characterized by unpredictability, high volume, variety and velocity and the value of this data to an enterprise will be commensurate with the data quality and the power of analytics done over it (Lavelle et al., 2011). Many enterprises have “reached a point where their ability to generate data exceeds their ability to consume that information. They have built capacity for analytics production, not insight” (Mazzei, 2017). The use of data visualization tools (e.g. Tableau, Raw, DataHero etc.) have been lauded as a means with which can address this disconnect. However, there is a marked distinction with regards to conceptualising personal analytics visualisation. Personal visualization “involves the design of interactive visual data representations for use in a personal context, and personal visual analytics is the science of analytical reasoning facilitated by visual representations used within a personal context” (Huang et al., 2015). This distinction is important as designing tools which support personal data analysis, particularly in the case of analytical amateurs, brings with it a nuanced set of challenges. For instance, “many data sources are easier available in organizations through their private IT infrastructure, so arriving to meaningful results may be more efficient than it would be for a selection of individuals with the need to deploy some techniques of data collection on multiple personal computers or mobile devices” (Huang et al., 2015). In order to advance the science of enterprise personal analytics, organizations must “develop methods and principles for representing data quality, reliability, and certainty measures throughout the data transformation and analysis process…where the goal is to facilitate high-quality human judgement” (Thomas and Cook, 2006). Furthermore, new tools are required “to make insights easier to understand and to act on at every point in an organization, and at every skill level” (Lavelle et al. 2011).

4.2. Perspectives

4.2.1. Company

This perspective represents forward-looking organizations who are looking to adapt to enterprise personal analytics and the consequent complexity inherent to this migration and how personal analytics is enabling individual and team work, while minimising risk to their business. Organizations can have different motivations for using enterprise personal analytics. According to Davenport (2014), the use of personal analytics “has much to teach organizations about alignment, performance improvement (individual and team) and business ecosystems”. For instance, an organization may want to increase innovation in their current business processes. The use of personal analytics can enable employees to identify and suggest improvements which can result in cost savings, better customer service and decreased employee frustration. These new improved processes and follow-on developments can become institutionalized across an organization. Furthermore, an organization may want to leverage the associated productivity benefits. Organizations can derive value from employees who use their personal analytic devices to productively link to resources while inside or outside normal working hours and company boundaries. Most significantly, in most businesses, "analytics have typically focused on operational or marketing issues and not on the human dimension of performance…even when companies do employ human resource analytics, their approaches are not sophisticated and have been applied only to individuals" (Davenport, 2014). There is also scope for organizations to use personal analytics in a team context so that they can evaluate across different teams compositions. Moreover, individual personal analytical data could be used strategically at a micro level for improving team performance at a macro level. Davenport (2014) outlines an example whereby companies would be able to use personal analytics to assess not just individual performance, but performance in context whereby organizations can determine how specific teams performs with or without a particular worker. This is called "plus/minus" analysis. However, there are a number of salient considerations which a company must take into account prior to commencing an enterprise personal analytics digital transformation journey such as: identifying the maturity and sophistication of the organization's analytical capabilities, determining the turnaround time for implementing such as strategy (e.g. quick wins vs longer-term goals) and implementing procedures for gaining strong organizational commitment towards the new personal analytics strategy.

4.2.2. Worker

This perspective represents individuals who perform roles which encompass responsibilities within a company for which they receive a salary. Personal analytics "can be considered a digital implementation of self-analysis practices and objectives…such digital implementation may facilitate the creation of new practices and objectives, which did not exist before" (Dobrinevski, 2013). The use of personal analytics can also facilitate a multitude of benefits for workers in terms of: increased understanding of how their "significant work" impacts the company's strategy and goals (e.g. business insight), facilitating meaningful working environments, enhancing career opportunities and improving job satisfaction (Harris et al., 2010; Harris et al. 2012). All of these factors are critical for retaining and engaging all types of workers. For instance, the use of modern digital technologies in the face of "changing characteristics of the generation of employees now entering the workforce, particularly their high levels of comfort with, and expectations about, social networking and consumer technologies, are seen as valuable tools in attracting and retaining these new hires" (Harris et al., 2012). How companies organise their analytical talent in a way that not only addresses the strategic and operational needs of the company but also provides opportunities for workers to derive value from the personal insights provided is essential (Harris et al., 2010). However, little is known about how to do this from an enterprise personal analytics context. Traditional enterprise personal analytic 'semi-automated' approaches leveraged "various computer-based tools and techniques to produce logs of events relevant to an individual. Such events may be simple registration of actions or more comprehensive measurements of various parameters at various moments of time" (Dobrinevski, 2013). However, in lieu of the recent trends discussed in section 3, workers have become increasingly comfortable with sharing their indiviual metrics as a means of enhancing their productivity (Smarr, 2012; Dobrinevski, 2013).

Subsequently, there are many open questions that would be of great interest. Some initial work has been done on how companies can organise their workers who have competencies in the use of analytics to derive business value from big data analytics (See Davenport et al., 2010; Harris et al., 2010), but we need a better understanding on how to best organise enterprise personal analytics efforts within the organization at an individual worker level and what core analytics processes the company must operationalise in order to support this (Grossman and Siegel, 2014). For example, a company can enable their sales employees to use the extensive data from their customer relationship management applications in order to assess and improve their performance. If, for instance, the most successful sales professionals tend to spend less than 10% of their time on lead generations, then average and low performers can adjust their daily work routines accordingly (Davenport, 2014).

4.2.3. Modality

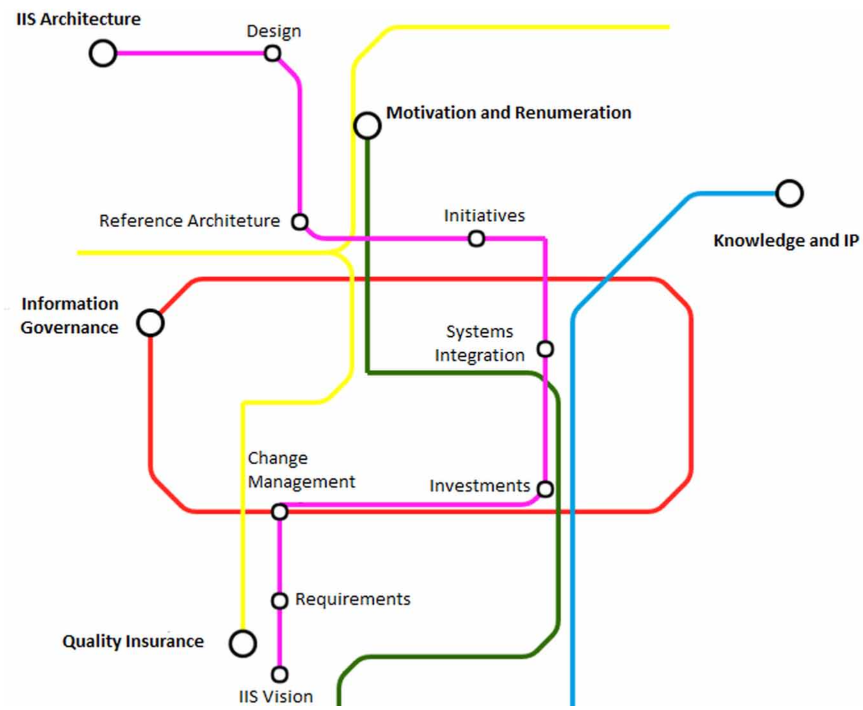
Modality refers to the mode through which personal analytics is experienced by the worker or is deployed by the company. This is becoming an increasingly important perspective as it has been argued that a 'intelligent digital mesh', which encompasses an expanding set of devices, individuals, information and services that are fluidly and dynamically interconnected to support intelligent digital ecosystems, is evolving around the individual" (Clearley, Walker and Burke, 2015). This digital mesh encompasses the following devices and tools: traditional computing and communication (e.g. digital, platform, desktop, mobile, tablet), wearable (e.g. health monitors, augmented and virtual reality displays), internet of things (e.g. consumer appliances, transportation and environmental sensors), and data storage (e.g. hard drives, cloud, usb). As this digital mesh evolves, a number of important questions emerge in the context of personal analytics modality. For example, how does the user experience fundamentally change and what digital technologies, security architectures and platforms are required to support this change? Most significantly, the ability for workers to use multiple modalities (e.g. multi-tasking, context switching) effectively is seen as a salient requirement for the successful development of a company's personal analytics strategy (Ingelbrecht and Herschel, 2015). According to Czerwinski, Horvitz and Wilite, (2004), "information workers often interleave multiple projects and tasks. Although workers may switch among tasks in a self-guided manner, a significant portion of task switching is caused by external interruptions (email, and internal messaging alerts, phone call, calendar reminder etc.)". Thus, questions with regards to user's experiences with recovery from interruptions and the nature and the density of interruptions in a personal analytics modality context are of interest.

5. USING THE FRAMEWORK

A nuanced characteristic of our 'grid' type framework (see Figure 2) pertains to the various permutations of research designs that can be operationalised. The first design is a multi-concern, single-stakeholder perspective denoted by the letter A. The second research design encompasses a single-concern, multi-stakeholder perspective denoted by the letter B. The final research design represents a single-concern, single-stakeholder perspective study denoted by the letter C. Given the siloed nature of the extant personal analytics research in conjunction with the dearth of research in the context of enterprise personal analytics, we encourage future research to populate each of the cells within this grid framework. This will facilitate the categorization of future research enterprise personal analytics studies within the IS discipline. To assist the process we have devised a number research questions (see Table 2) which we are of the opinion merit further scrutiny.

From a practitioner perspective, we have also devised a visual mapping artefact (Figure 3) which we have coined as the "enterprise personal analytics metro map" which could be used by companies to plan and map their enterprise personal analytics digital transformation journeys. This metro map depicts possible journey pathways which companies must navigate. For illustration purposes we have completed the journey for the IIS architecture concern raised in this paper. This specific journey which comprises possible 'route stops' which must be considered by organizations. We encourage future research to not only identify these 'route stops' for the other concerns addressed in this paper from a qualitative perspective but also from a quantitative perspective to identify if there are specific paths on the metro map which traverse each route stop once and only once. If so, this path is called an 'Euler circuit' (Euler, 1741) a term derived from the famous Konigsberg bridge problem.

Figure 3. Enterprise personal analytics metro map



6. CONCLUSION

We have presented an enterprise personal analytics framework comprising five specific concerns in the context of several perspectives. These concerns may represent the greatest hurdles in the broader adoption of the self-analysis culture and practices within an enterprise setting. Our framework encourages a systematic focus and strives for a common understanding of the role of individual personal analytics within the enterprise. The following limitations should be kept in mind when considering the findings of this paper. Personal analytics as an academic topic of study is relatively young, and there are few well-established theoretical frameworks or unified discourses. While it is felt that the sample of publications is representative of the personal analytics literature, there may be some bias associated with the narrow focus of the research resources under review. In summary, this paper offers the following contributions to the emerging IS and business intelligence literature on personal analytics and its potential use in an enterprise setting: (1) it discusses important analytical developments which have shaped the emergence of the enterprise analytics concept, (2) it provides a holistic framework which aims at synthesising and advocating future research in the promising area of enterprise personal analytics, (3) it identifies possible research questions aimed at highlighting how the framework can be used and (4) it provides an overview of a proposed visual mapping artefact aimed at assisting companies with their enterprise personal analytics digital transformation journeys.

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