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Enterprise Personal Analytics: The Next Frontier in Individual Information Systems Research

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Abstract

Organizations have long used analytics to improve performance. Modern enterprise technological landscapes are being impacted by the increasing individuation of information systems (IS). One promising technological advancement in this regard will be the use of personal analytics within an enterprise setting. While traditional organizational intelligence metrics deliver a big picture of structures, processes, and roles, more detailed and personalized analytics enables employees to scrutinize their personal productivity in terms of their desired versus their actual way of working. Personal analytics empowers individuals to analyze and exploit their own data to achieve a range of objectives and benefits across their work (e.g., productivity, quality, performance) and personal lives (e.g., sleep, exercise, health). This topic has been only minimally analysed in IS research. Furthermore, there have been increased calls by academics to investigate the individuation of IS which has largely gone unnoticed in the IS research discipline. While the mainstream application of personal analytics in an organizational setting remains relatively niche, we believe its impact will fundamentally change enterprises across all sectors. Thus, in the scope of this monograph, we shall focus on this emergent category of analytics which we refer to as "enterprise personal analytics" which encompasses the concept of organisations enabling their employees to use their individual analytics to manage their digital working lives from descriptive, diagnostic, predictive and prescriptive points of view. Our comprehensive review of the existing empirical research on the use of personal analytics within an organizational setting identified that the only consistency pertaining to the concept was inconsistency. Therefore, this monograph offers the following theoretical and practical contributions:

1. We present an overview of specific analytics trends which have shaped the personal analytics landscape which include: learning analytics, the quantified self, human-centric analytics, gamification, sports analytics, personal cloud and Neuro IS.

2. We present a framework, derived from a comprehensive review of the personal analytics literature, which consists of various combinations of research stakeholder perspectives and concerns. This framework can be used to guide and coalesce future IS research on enterprise personal analytics.

3. We provide an overview of possible research questions aimed at highlighting how the framework can be used.

4. We propose a visual mapping artefact aimed at assisting companies with their enterprise personal analytics digital transformation journeys.

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Introduction

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"We're in the age of auto-analytics, or the capturing and analysis of personal productivity data".

Thomas H Davenport [2014]

According to Watson [2013] "there is considerable "buzz" about analytics. It is the topic of numerous articles, books, web seminars, white papers, and research reports and there is growing evidence that analytics is becoming an important component of organizational success". 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). Organizations have long used analytics to improve performance. Indeed, research shows that top performing organizations use business analytics five times more than lower performers do [Lavelle, et al. 2011]. In 2016 the business analytics industry was worth an estimated US $130 billion. For example, it is estimated that industrial sectors such as discrete manufacturing, process manufacturing, telecommunications, and healthcare manufacturing will invest a combined total of $101.5 billion in business analytics by 2020 [IDC, 2017]. One promising technological advancement in this regard will be the use of personal analytics. While traditional organizational intelligence metrics deliver a big picture of structures, processes, and roles, more detailed and personalized analytics enables employees to scrutinize their personal productivity in terms of their desired versus their actual way of working. Personal analytics "empowers individuals to analyze and exploit their own data to achieve a range of objectives and benefits across their work (e.g., productivity, quality, performance) and personal lives (e.g., sleep,

exercise, health)." Personal data can relate to biometrics, personal finance, social media activities, health status, behaviors, emotional states, mobility, personal interest areas, and so on. In Chapter 3, we will highlight how advances in analytical and business intelligence technologies have resulted in the emergence of a number of personal analytics trends which have resulted in a dramatic increase in the manner with which consumers use personal analytics in their everyday lives (e.g. wearable technology). As a result of the multitude of benefits which consumers are deriving from the use of personal analytic technologies, organizational interest in personal analytics is also beginning to gain traction. In this article, we will focus on an emergent personal analytics concept that we call "enterprise personal analytics" (or EPA, for short). EPA can be defined as the manner with which "organizations enable their workers to use their personal data to manage their digital working lives from descriptive, diagnostic, predictive, and prescriptive points of view".

Like many information systems (IS) researchers [e.g. Davenport, 2014; Lee and Balan, 2014; Clohessy and Acton, 2017b] and IT analysts [e.g. Ingelbrecht and Herschel, 2015; Kleynhans, 2015] we believe that the emerging concept of EPA has the potential to become the new frontier of competitive differentiation. EPA may be of interest to a multitude of organizational sectors such as manufacturing, utilities, energy, and aviation. For instance, EPA can enable skilled and unskilled industrial operators to analyze their own personal data to understand why they're making the choices they're making and then to combine their human expertise with the underlying objective data to create new operating procedures and processes [Bell and Bell, 2016]. Wearable technology is increasingly being used in the manufacturing industry for employee safety, employee monitoring, video applications, field service, and plant monitoring [Leavitt, 2017]. Organizations can also leverage the rich insights provided by nonverbal data - which can be captured by personal digital monitoring technologies for time management (e.g., Microsoft MyAnalytics), facial coding (e.g., Affectiva, Microsoft Emotion), brain imaging (e.g., Neurosky, Emotiv), pupillometry (e.g., Tobii, Eye-Square), and physiological monitoring (e.g. Empatica, Fitbit) - to improve efficiency and attention management, increase well-being, and reduce mistakes. Enterprises can use all this EPA data and more to provide actionable insights that directly support their most important business decisions (automating a process versus losing employees' tacit knowledge, rewarding star players/teams, enhancing the physical and mental well-being of employees, etc.).

However, the use of personal analytics in an enterprise setting is different from its use in other environments (e.g., private use). This has implications for which aspects of personal analytics should be considered in an enterprise context. Thus, further research is needed to elucidate both the benefits and most significantly the challenges that organizations could face when adopting EPA digital initiatives. To advance the EPA concept we conducted a comprehensive literature review (see Chapter 2) of the extant empirical research of the use of EPA in organizational settings. We identified five specific concerns pertaining to the use of personal analytics in an enterprise setting: individual information systems architecture, knowledge and intellectual property, motivation and remuneration, information governance, and quality assurance. As EPA involves different stakeholders, it is useful to study the concept from juxtaposing perspectives. Our analysis has revealed three relevant perspectives: company, worker, and modality (i.e., the mode through which companies enable their workers to use personal analytics). Consequently, we have used a two-dimensional grid (concerns vs. perspectives) to define a research framework that can be used to guide future IS EPA research efforts (see Chapter 6). We have also devised a companion visual mapping artefact (see Chapter 7) which we have coined the "EPA digital transformation metro map" which depicts possible routes which companies must navigate for the five concerns across the three perspectives raised. Ultimately, both artefacts have been designed to advance the concept of EPA to assist organizations to embrace its potential while concurrently avoiding the pitfalls [Clohessy and Acton, 2017a].

To summarize, this monograph examines an emergent category of personal analytics which we refer to as "enterprise personal analytics" which encompasses the concept of organisations enabling their employees to use their individual analytics to manage their digital working lives from descriptive, diagnostic, predictive and prescriptive points of view. The monograph is structured as follows. First, the individuation of IS is examined. Second, the methodology is explained. Third, an overview of the recent personal analytical trends is provided. Fourth, an EPA research framework comprising specific perspectives with regards to stakeholders and concerns is delineated. Finally, the monograph concludes with a discussion pertaining to theoretical and practical implications and limitations.

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Methodology

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The primary objective of our literature review was to analyse the extant empirical research on the use of personal analytics in organizational settings. 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]. Our motivation was to produce a well-rounded understanding, which is currently lacking in the information research (IS) field, and ultimately create a consensus on the enterprise personal analytics concept by carefully describing and then contrasting and comparing an array of sources on the topic [Heyvaert et al., 2013]. Our coherent review of the literature was greatly assisted by our coherent conceptual structuring [Webster and Watson, 2002] of the enterprise personal analytics topic which will we will now discuss in the next section.

2.1   Literature Review Process

We conducted a comprehensive survey of the literature to produce a systematic deductive analysis of the concept of enterprise personal analytics [Heyvaert, et al., 2013]. 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 and data collection process we used a three-stage literature mapping protocol (see Figure 2.1). as prescribed by Kitchenham and Brereton [2013] to search, select, appraise and validate the literature. This mapping protocol ensured that we did not overlook relevant literature which may have been categorised under different headings. This protocol also helped the researchers

to define the boundaries in which our review was conducted (e.g. inclusion and exclusion criteria). 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 status of personal analytics research: EBSCOhost, JSTOR, ProQuest, Google Scholar, PubMed, Scopus, and Web of Knowledge (Table 2.1). We selected these specific databases because of the multidisciplinary nature of personal analytics and IS research. Furthermore, these databases have been used by IS researchers as sources for other systematic literature reviews [Vom Brocke et al., 2015]. Most significantly, these databases enable the seamless identification of influential research papers from the top basket of IS journals. Prior to establishing defined search parameters, we experimented with combinations of operators and search terms [Kitchenham and Brereton, 2013]. These experiments across the selected databases improved our comprehension of search combinations which worked effectively. 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. Given the dearth of research pertaining to the enterprise personal analytics concept, grey literature research resources (e.g. conference proceedings, research reports, issue papers, white papers etc.) were also included. Inaccessible research sources were excluded in cases where the library did not access to a full-text version or where the library was not subscribed to a publishing resource. 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 s*tages 1* and *2* and comprised three main tasks: search process validation, backward snowballing and researcher consultation" [Kitchenham and Brereton, 2013].
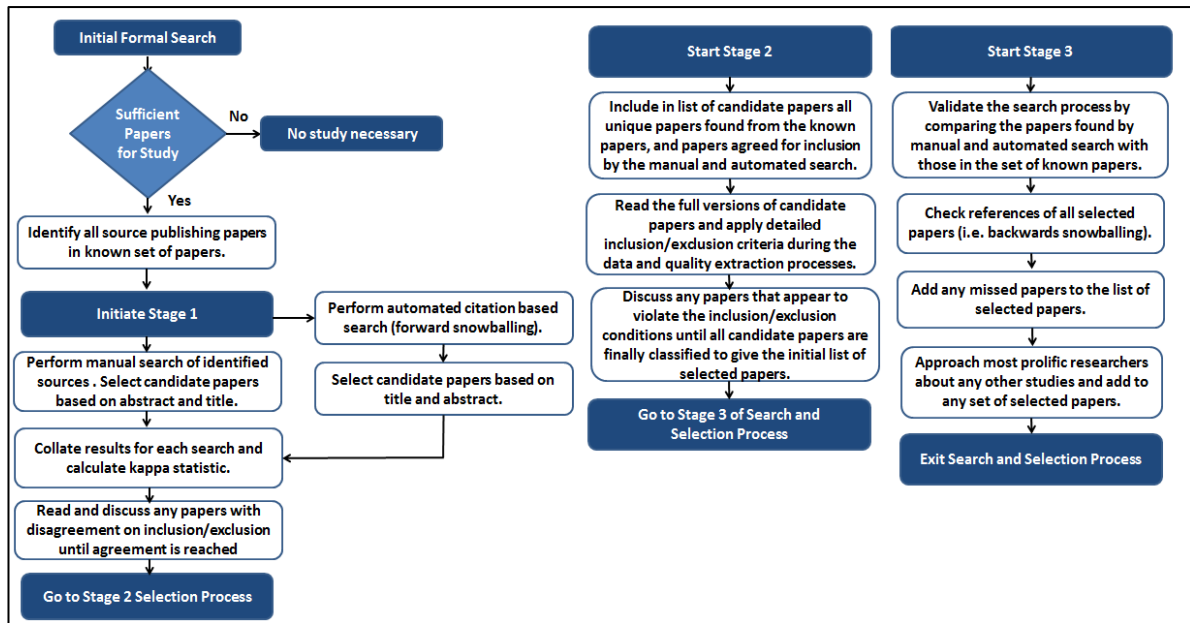
Figure 2.1 Literature Review Mapping Process. Adapted from Kitchenham and Brereton [2013]

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

Table 2.1 Databases accessed, query method, and search results

In terms of exclusion criteria, *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 terms of inclusion criteria, we placed a robust emphasis on the use of personal analytics within an enterprise setting. Consequently, a total 563 articles were discarded which resulted in a final total of 76 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. This stage of coding involved scrupulous familiarisation and interrogation of the data. Due to the tentative nature of the codes and concepts which emerged during the initial stages of the open coding process, the researchers constantly compared the qualitative data for similarities and variations (Myers, 2013). 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]. Axial categories and subcategories were developed through a coding paradigm of causal conditions, strategies, context or intervening conditions. This stage of the analysis also focused on intended and unintended consequences. Hypothetical relationships which emerged were repeatedly checked in a deductive procedure using the collated data. 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. 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 76 research resources, which formed the backbone of our literature review, were full text reviewed and coded to create an enterprise personal analytics research framework which will be presented in Chapter 4.

From the initial study design, through to the development of the methodology and the reporting of the findings, the study made use of an audit trail and audit process [Schwandt, Lincoln and Guba, 2007]. This ensured that the study was underpinned by rigour, authenticity and neutrality. To ensure validity and reliability during the review and coding process we: (1) used a three stage-literature mapping protocol, (2) established a chain of evidence, (3) used NVivo for coding and independent inspection of the data and (4) created a literature search checklist. Both the literature review and the coding processes involved all the authors and were coordinated by the main author. For instance, during the data collection process, one author extracted the data, and another checked the extraction. Similarly, during the literature search process, once one author had completed a search of a specific database using the defined search parameters, another author replicated this approach to ensure consistency. When a disagreement arose, the issue was discussed until we reached an agreement. In Chapter 3 we provide an overview of the significant technological developments and trends which have shaped the personal analytics landscape.

3

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Recent Trends in Personal Analytics

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In this chapter, we illustrate how advances in analytical and business intelligence technologies have resulted in the emergence of a specific of personal analytics concepts which traverse multiple disciplines. Armed with technologies such as smartphones, fitness trackers, drones, and virtual reality, the digitized individual leaves behind a vast reservoir of data about themselves and their surroundings. EPA aims to turn such digital traces into value for the individual (e.g. using personal analytics technologies to identify skill gaps) the enterprise (e.g. identifying customers patterns associated with product locality), and even society (e.g. gamify fitness trackers to promote public health). Recent advances in EPA present enormous opportunities at all levels, along with significant issues, none more important than privacy. The recent trends in EPA, along with the opportunities and challenges, are discussed throughout this chapter.

3.1   Individuation of IS

There is no doubt that IS are evolving rapidly, so much so that careers once thought to be the preserve of smart humans such as surgeon, pilots, and lawyers, are now being tasked to AI powered machines (Mitchell & Brynjolfsson 2017). In terms of our everyday lives, the biggest evolution has been in the individualization of IS, which commentators generally define as the ability of the person themselves to seamlessly draw upon the immense power of ICT in all aspects of their lives, from booking flights, to filing tax returns, to recommending what TV series to watch [Baskerville 2011]. A typical smartphone of today is significantly more powerful than all the computers used by NASA to send man to the moon. Indeed,

many of today's most celebrated entrepreneurs, from Mark Zuckerberg, Larry Page, and Sergy Brin started billion businesses from their own bedroom or garage with little more that a laptop and a connection to the Internet. For activities as diverse as entertainment, work, travel, dating, and exercise, there seems to be no aspect of our individual lives not influenced by the ever-growing power of IS. But it has been argued that this individuation of IS has largely been ignored by the IS research community [Baskerville 2011] with a fixation on the organization prevailing throughout the recent decades. But now, within organizations the individuation of IS has never been more important with leaders struggling to govern worker BYOD demands [French et al. 2014] and the shadow IT environment [Fuerstenau & Rothe 2014]. Emboldened with deep analytics, the individual or quantifiable self can now be considered a unique form of organization which should be a central foci for the IS community.

Drawing from the sociological theories of structuration and individuation, Gaß et al. [2015] conceptualize the factors and mechanisms that influence individuation in IS. As depicted in Figure 3.1, the conceptualization is characterized by three connections between key entities - individual IT identity, social IT identity, and individual IS. Applying this conceptualization enables us to understand how personal analytics contributes to the understanding of individuation in IS. Firstly, in terms of *contributions to self-determined composition,* personal analytics enable the individual to be more aware, and better understand their own biographies, thus enabling them to tailor the environment to align with their own idiosyncrasies. For example, researchers at the Technical University of Berlin have developed a neuro-adaptive system, incorporating real-time analytics of brain activity, which detects when information displayed on a screen violates the user's expectations, and then automatically adapts to synchronize with those expectations [Zander et al. 2016]. Second, personal analytics contributes to *institutional requirements and constraints* as emerging evidence demonstrates individual employees now have more control to visualize personal data and self-optimize with or without the support of the organization, which profoundly alters how they reflect on themselves, on others and on their daily lives [Ruckenstein 2014]. Thirdly, personal analytics influences *socialization.* Exercise tracking apps such as Strava, which reward the exerciser and displays trophies and leaderboards to reward competitive performance, are altering how groups of users perceive their environment and those around them differently and therefore act differently as they move through it [Hafermalz et al. 2015].

It has also been argued that the prevalence of personal analytics will lead to self-tracking cultures aligned to the belief that masses of data leads to superior knowledge [Lupton 2014].
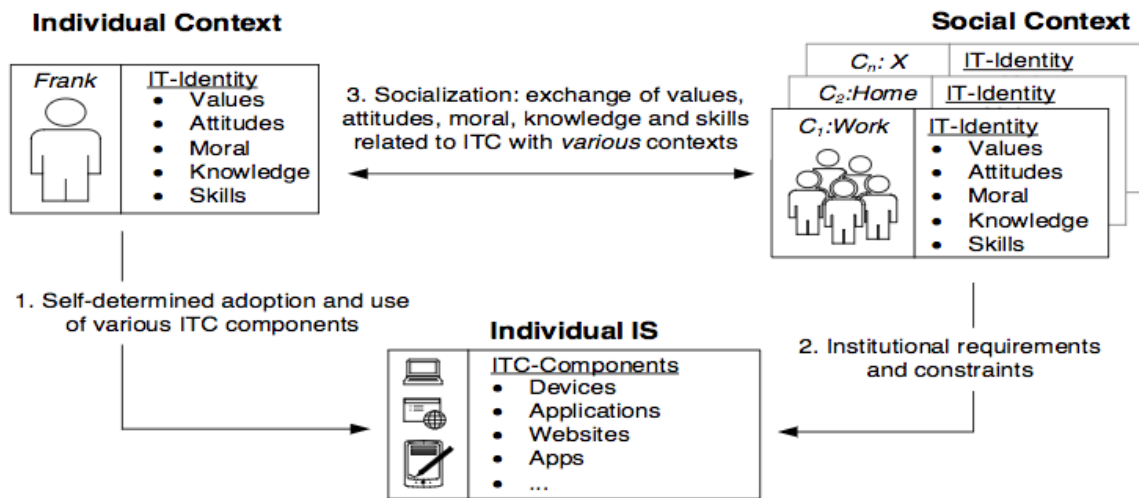

Figure 3.1 Meta Theory for Individuation in IS [Taken from Gaß et al. 2015]

While the individualization of IS has been progressing over the past 2 -3 decades, a particular form of this individualization, the quantified self, has only emerged in recent years due to advances in personalized hardware and software. It is to the quantifiable self we now turn.

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). According to Swan [2012] "a key contemporary trend emerging in big data science is the quantified self (QS) - individuals engaged in the self-tracking of any kind of biological, physical, behavioural, or environmental information as n = 1 individuals or in groups". Engagement in self-monitoring methods is not a novel phenomenon. The quantified self-movement aligns itself with similar concepts which have been proposed by philosophers such as Epicureans, Heidegger and Michael Foucault who highlighted the importance of self-reflection and the use of self-knowledge for personal development [Melanie, 2013]. Consequently, from a historical perspective people, have always tracked personal data in lieu of the absence of technology. Ultimately, a proactive stance is taken towards obtaining personal information encompassing specific metric variables (see Table 3.1) and acting upon it. Currently, 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]. The modern evolution of the self-quantified concept was originally coined in 2007 by Kevin Kelly and Gary Wolf who described the "quantified self" as a movement which promotes and symbolizes improvement through awareness and self-discovery [Rosenbaum, 2015].

Quantified Self Measurement Categories	Metric Variables
Physical activities	miles, steps, calories, repetitions, sets, METs (metabolic equivalents)
Diet	calories consumed, carbs, fat, protein, specific ingredients, glycaemic index, satiety, portions, supplement doses, tastiness, cost, location
Psychological states and traits	mood, happiness, irritation, emotions, anxiety, self-esteem, depression, confidence
Mental and cognitive states and traits	IQ, alertness, focus, selective/sustained/divided attention, reaction, memory, verbal fluency, patience, creativity, reasoning, psychomotor vigilance
Environmental variables	location, architecture, weather, noise, pollution, clutter, light, season
Situational variables	context, situation, gratification of situation, time of day, day of week
Social variables	influence, trust, charisma, karma, current role/status in the group or social network

Table 3.1 Augemberg [2012]

The primary motivations for quantified self-monitoring are wide ranging. Studies have demonstrated that early market based quantified self-monitoring consumer devices were used predominantly to resolve lifestyle issues such as weight management, sleep quality, work productivity etc. [Swan, 2012; Melanie 2013]. The ultimate benefit of these devices was that they enabled consumers to engage in introspection with regards to their personal health information which is in itself an intervention [Didžiokaitė et al., 2017]. Further benefits of quantified self-tracking include empowerment, reasonability taking as well as improved health and wellness outcomes [Simon and Kelly, 2017; Wahl-Jorgensen et al., 2017].

Methods and tools for quantified self-tracking range from manual pen, spread sheets and paper techniques to more sophisticated automated tracking devices such as mobile applications and specialized information systems. Modern information and communication technology advances are resulting in the emergence of an increasing number of new personal data streams. These data streams are being generated because of the increasing commercial availability of internet of things sensors, quantified self-monitoring devices, social media data

and health and fitness social networks. More sophisticated self-monitoring devices are also coming down the pipe line (e.g. biometric scanning, eye tracking, mood and emotion measurement and consumer EEGs). These devices will create further new personalized data streams.

We will now provide an overview of how specific quantified self-monitoring devices are impacting consumers:

- From a medical perspective, the use of mobile health (mHealth) and wearable health applications for incentivizing health behavior change continues to grow at an unprecedented rate (Kenny et al., 2017). 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. According to Bert and Giacometti, [2014] 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]. Furthermore, extant applications are being used by consumers to monitor various chronic conditions (e.g. asthma, diabetes, pain). These applications serve as digital journals enabling users to log symptoms, assess various treatments and reactions to specific environment stimuli [Simon and Kelly, 2017].

- From an education and development perspective, 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 recognize other people's emotions [Gillam et al., 2015]. A self-monitoring device known as MotivAider is currently being used by students and children to improve their attention spans and to motivate positive behavioral changes.

- From an enterprise perspective, organizations are using personal analytical data to provide actionable insights that directly support their most important business decisions (e.g. automate vs tacit knowledge loss, rewarding star players/teams, enhancing the physical and mental wellbeing of employees etc.). For instance, the use of wearable technology is increasingly being used for employee safety, employee monitoring, video applications, field service, and plant monitoring[5]. Furthermore, the rich insights provided by nonverbal data, which can be harnessed by personal digital monitoring technologies for time management (e.g. Microsoft MyAnalytics), facial coding (e.g. Affectiva, Microsoft Emotion), brain imaging (e.g. Neurosky, Emotiv), pupillometry (e.g. Tobii, Eye-Square) and physiological (e.g. Empatica, Fitbit), can be leveraged by organizations to improve efficiency and attention management, increase wellbeing and reduce mistakes.

Whereas the preceding paragraphs provided an overview of quantified self concept and its associated benefits with exemplars being given of specific applications, we will now discuss the concerns and barriers which have polarized arguments regarding the phenomenon. Firstly, critics have articulated a number of broader ethical and societal issues. For example, critics argue that the quantified self concept is blurring the traditional boundaries between public and private surveillance [Swan, 2012; Sharon, 2017]. Sharon [2017] opines that the quantified self-movement extends the 'net of surveillance' by encouraging intrusive surveillance practices via the sharing of personal data on social media and other digital platforms". Second, in lieu of the potential benefits of self-monitoring practices, practical and mindset barriers are serving to stagnate the widespread adoption of quantified self-tracking. From a practical perspective, the market is currently saturated with self-tracking devices which have failed to capture the attention of consumers as a result of monitoring accuracy, high product prices, high degree of manual input effort, comfort and usability issues. From a mind-set stance, consumers must overcome cultural, sociological and psychological hurdles. For instance, the value proposition of monitoring health data the absence of real and visible results is seen as onerous and unappealing. Moreover, the role of health protection and monitoring is seen as being the responsibility of care providers, clinicians, hospitals, physicians and so on. What is lacking from current market offerings are technologies which learn with and adapt to the user experience. However, some progress has been made in this field of human-centric personal analytics.

3.3   Human-Centric Personal Analytics

Also referred to as context-aware computing, human centric personal analytics refers to a class of mobile systems which can sense their physical environment and adapt and make changes accordingly. By context we mean, data which is obtained from a mobile device about an individual and their surrounding environment. This computational deductive capability subsequently frees up or focuses the user's attention. A confluence of ubiquitous and pervasive technology trends has precipitated the proliferation of a wide variety of sensors in the possession of the average individual [Srivastava, Abdelzaher and Szymanski, 2012] which has culminated in the emergence of a concept known as human-centric personal analytics. The primary objective of this new phenomenon is to investigate how context aware mobile applications can be used to "automatically adapt based on what the user is doing, what they feel like doing, and what they should be doing" [Lee and Balan, 2014]. 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)." This human-centric approach to personal analytics facilities the provision of new and interesting insights into mobile users and their interactions and the physical world [Mikusz et al., 2016]. 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-centhuric personal analytical mobile applications include BeWell, Walksafe, EmotionSense, MoodScope, MoodSenese and StressSense. In the case of StressSense, an application which can detect a user's stress levels by using a smartphone's microphone to analyze vocal stress, preliminary evidence suggests that the application is 81% accurate when used indoors and 76% accurate when used outdoors [Jaffe, 2012]. MoodSense is a social media mobile application which can infer its owner's internal mood based on historical mobile information. The service enhances context-awareness by creating a breadcrumb trail or clues pertaining to an individual's mental health. This evolution of mobile sensing capability which can infer the mental health of users

opens a multitude of nascent opportunities for mobile devices (LiKamWa et al., 2011). Walksafe uses both the front and rear camera and the embedded accelerators of a mobile phone to detect vehicles, pedestrians and cyclists approaching the user and alerts them of a potentially unsafe situation. Walksafe operates on a trifecta intersection level of vision, learning and mobile computing.

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. According to Cohen et al., [2004], "our day-to-day living experiences, the activities of an individual worker, and the processes of a large corporation can all be simplified by computing systems that are aware of an individual's context". 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.). Recently, Australian engineers created a smart desk light status indicator known as the FlowLight. This device automatically detects when a worker is 'in a state of flow' or 'in the zone' and illuminates in a red light alerting co-workers not to disturb them. A green light signifies that the worker can be approached. Flow is a multifaceted and polymorphous concept which represents a state of 'optimal experience' where the extent of participation and pleasure in an activity is determined by perceptions of intrinsic interest, user control, arousal of curiosity, and attention focus [Csikszentmihalyi, 1975]. The smart device which minimises the risk of flow interruptions currently uses mouse and keyboard indicators to assess a worker's flow state. Safe guards are in place to prevent the device from becoming a competitive indicator. The engineers are currently investigating more sophisticated biometric measures such as heart rate, pupil dilation, eye blinks and brain wave activity. Furthermore, Mikusz et al., [2016] discuss a specific human-centric personal analytics project which used simple mobility traces and models in conjunction with an IoT energy hub to monitor the energy impact of students and staff. This nuanced analytics approach provided new insights pertaining to the energy impact of individuals rather than buildings on energy consumption rates around a college campus.

Smart glasses have also been cited as examples of devices which can be leveraged to provide new personal analytics insights through human cognitive enhancement [Huang, 2013; Benessia and Pereira, 2015; Hoffmann et al., 2016]. Table 3.2 outlines the main benefits associated with smart glasses in terms of providing cogent human-centric insights.

Smart Glasses Potential Benefits
Smart-glasses may become an extension of human body and mind and enhance our interaction with the environment.
Making learning more efficient or create new learning modes. However, the outcomes of learning with smart-glasses are mixed.
Provide safety and security, e.g., for persons with various forms of impairment, such as detecting hazards for persons with visual impairment, or in the industry.
Smart-glasses may increase situational awareness, multitasking abilities, and orientation.
User empowerment, self-sufficiency and inclusion in decision making, and new business models through open hardware, open software, and open data.
Be a valuable extension of the human brain and predicting cognitive states.
Compensate for impaired functions, such as landmark identification for persons with reduced visual ability increasing their quality of life.

Table 3.2 Adapted from Hoffmann et al., [2016]

Google Glass is an example of a smart glass device which has received both mainstream recognition and notoriety. The Google Glass platform is currently being used by medical professionals as an augmented realty (AR) device to deliver better health care to patients. These smart AR glass platforms have dramatically improved existing medical workflow practices in terms of reducing errors (e.g. remote monitoring of digital checklists), time savings (e.g. real-time access to patient information through hand gestures), documentation (e.g. automatic data entry), education (e.g. use of digital recording for tacit knowledge transfer) and new collaboration opportunities (e.g. connecting physicians to ultra-specialists in real time). However, the mainstream adoption of smart glasses devices including the Google Glass have been hampered by safety, security, privacy, ethical, health and concerns [Hoffmann et al., 2016] in conjunction to consumer preference for alternative augmented reality applications (e.g. Pokémon Go) and the (re)emergence of virtual reality products (e.g. Microsoft HoloLens). While the challenges associated with such technologies are not to be underestimated, the potential benefits, particularly advancing the learning capabilities of users, is enormous.

3.4   Learning Analytics

The emergence of the learning Analytics concept in the last decade has been a significant development in the technology-enhanced learning landscape. The learning analytics concept has its foundations deeply rooted in a multitude of disciplines such as business intelligence, web analytics, recommender systems and educational data mining [Ferguson, 2012]. The global learning analytics market is forecast to reach $2.44 million by 2019 [Infiniti, 2015]. 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 Society for Learning Analytics research have extended this definition to outline why the collection of this type of data is needed "for the purposes of understanding and optimizing learning and the environments in which it occurs" (SoLAR, 2017). 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]. Coupled with rapid advancements in software and analytical methods, the emergence of big data sets In formal education settings, which are derived from student's interactions with educational software and online learning platforms, holds promising potential [Siemens and Baker, 2012] for several main interest groups: external bodies (e.g. governments), educational institutions and teachers/learners (e.g. pedagogic). For example, because of governmental, competitor, funding, accreditation and global ranking pressures, educational institutions are increasingly seeking out sophisticated method/tools which can measure, demonstrate ad improve performance [Ferguson, 2012]. Subsequently, with growing interest in learning analytics and educational data mining, 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]. For instance, the Blackboard system encompasses education analytics module functionality which provide academic institutions with a complete data warehousing and reporting solution in support of teaching and learning. There is evidence to suggest [See Sclater and Mulan, 2017] 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. Human Capital data management systems such as Oracle Human Capital Management, IBM Cognos Performance Talent Analytics, D2L, SAP SuccessFactors and SAS Human Capital are examples of enterprise cloud-based virtual learning management software which enables organizations to operationalize 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]. According to a Global survey conducted by SuccessFactors [2014] of millennial and non-millennial employees, 30% of the sample indicated that they wanted feedback on their performance at least weekly with 90% indicating that they wanted feedback on a monthly basis. Self-learning through personal analytics has been cited as exemplar method for unlocking an employee's potential and maximizing performance by enabling them to learn rather than being taught [Willyerd, 2015]. As industry and practitioner reports continually advocate that talent management is both critically important and also challenging for all organizations, regardless of their industry or their size, more and more enterprises are increasingly recognising the value of employee data and analytics. Further research is required in order to improve our understanding of how these organizations are enacting their talent management analytics initiatives.

Furthermore, there are a number of challenges which learning analytics need to overcome [Ferguson, 2012, Siemens and Long, 2012]. First, comprehension and optimizing learning requires an effective understanding of how learning is implemented and supported (e.g. technologies, information systems etc.). Furthermore, knowledge of factors such as affect identity and reputation is paramount [Ferguson, 2012]. Second, to effectively understand the challenges faced by learners, providers of virtual learning environments will have to move towards the analysis of increasingly complex data sets and combinations of data sets including biometric, mood, emotion, neural and mobile data [Ferguson, 2012]. Further research is required to investigate what these challenges look like in different learning

environments and from the perspectives of difference learners [Siemens and Long, 2012]. Third, it cannot be reiterated enough how important it is to focus on the perspective of the learner. Analytical methods/tools and virtual learning environments adoption rates by academic institutions are still at an embryonic stage. Moreover, personalized methods of reporting and visualizing analytics have still to reach maturity. Transparency, the realignment of extant work metrics from substantive to formative measures, simplicity and trust are seen has key determinants which will impact the success or failure of learning analytics in the future [Ferguson, 2012]. Finally, to overcome these trifecta of challenges, ethical questions pertaining to data ownership and governance become of paramount significance [Clohessy and Acton, 2017a]. The emergence of the General Data Protection Regulations (GDPR), which replaces the existing data protection framework under the European Union (EU) protection directive, emphasizes transparency, security and accountability with regards to the processing of data for all individual within the EU. From a student learning analytics perspective, GDPR attaches new conditions with regards to consent [Sclater, 2017]. Academic Institutions must inform students and staff of the personal information being collected about them and the purposes, including any results of learning analytics, for which it may be used" [Sclater, 2017]. We will discuss the wider ramifications of GDPR in Chapter 4.

One industry which has been at the forefront of the learning analytics movement is professional sports. Made famous by the Brad Pitt movie 'Moneyball', the rise of the Oakland A's from baseball obscurity to genuine challengers was allegedly driven by the adherence to the analytics philosophy. As now discussed, many of the advances in EPA have first seen the light of day in the sports context.

3.5   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 scrutinized 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 characterized by a similar ethos of competitiveness, incentives, individualism, camaraderie and achievement [Peters, 1996, Dovey and Singhota, 2005, Soane, 2014]. Furthermore, Clohessy [2016] discusses how the concept of in game sporting team momentum can be used by software development teams as a means of sustaining momentum during software development projects. Momentum is defined by the Oxford English Dictionary as "the impetus and driving force gained by the development of a process or course of events" [Harker et al., 2013]. According to Adler [1981, pg.9], "in his play by play rendition of the struggles between the contending teams of Trojans and Greeks, Homer was the first sociologist to take as a topic of analysis the phenomenon of momentum – the forces that move people to extraordinary action". Momentum is a "pervasive force in companies, whereby past practices and, trends and strategies tend to keep evolving in the same direction…eventually reaching dysfunctional extremes" [Miller and Friesen, 1982]. From an entity perspective, traders currently use technical analysis techniques and indicators such as the relative strength index, price rate of change, stochastics and moving average convergence divergence to measure the strength of an assets momentum and its ability to sustain positive momentum. From an individual and team perspective, enterprises are now exploring how they can sustain positive momentum in modern complex and dynamic environments.

For example, Reel [1999] identified momentum as one of the most critical success factors for successfully managing software development projects. Momentum changes often during software development projects. These changes add up quickly, so it is crucial to quickly offset the negative shifts with positive ones". Momentum is often used as a metaphor for being a powerful change agent in modern software development project failures whereby the term is commonly used to describe how "the team lost momentum" or "the shift in momentum had disastrous consequences for the project".

There is evidence to suggest that enterprises could potentially adopt sporting analytical practices and procedures to sustain positive momentum within specific projects. Sports analytics is defined as "the management of structured historical data, the application of predictive analytic models that utilize that data, and the use of information systems (IS) to inform organizational decision makers and enable them to help their teams in gaining a competitive advantage on the field of play" [Alamar and Mehrotra, 2011]. In the context of sports analytics, a sporting information system "when designed and implemented correctly, typically allow for visualization and interactive analysis of relevant information from multiple sources in one place, organized in a meaningful way to provide insights for decision makes" [Alamar and Mehrotra, 2011]. For instance, a cutting-edge data driven decision sport platform combines unstructured information from scouting reports, summary reports from multiple data sources and results from predictive models.

In a sporting context, momentum is a force that dictates the ebb and flow or a competitive event [Higham, Harwood & Cale, 2005]. According to Fry and Shukairy [2012] "the concept of momentum is often cited by coaches, players, commentators and fans as a major factor in determining the outcome of the game and, consequently, in-game decision making". The sporting literature reveals that the most successful athletes and teams possess a critical ability to heavily influence the ebb and flow of momentum using team and individual metrics during a sporting contest. For example, they can not only sustain stability within a contest by operationalizing coping strategies to smooth out the impacts of critical incidents but they also demonstrate a cogent ability to rapidly restabilize their performance to optimal levels when a critical incident does disrupt their normal momentum (Hughes et al., 1998, McGarry, et al., 2002, McGarry, 2009). American football teams use personal analytical metrics to identify how precepting events or critical incident impacts performance and explore how that impact causes a shift in momentum. Moreover, technology companies such as Accenture can measure in game team momentum through their live analytical dashboards by measuring performance metrics over the duration of a game.

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. Table 3.3 highlights how P&G have implemented modern sporting analytical processes within their organization. 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 analyze their own performance metrics in order to improve on them. Furthermore, P&G recruit employees whose skills sets and personality trait metrics mesh well with employees who already work within the company. This specific team building method has been used by successful sporting teams such as the Chicago Blackhawks who recruit players whose style of play and skill set analytics match those who are currently playing on the team squad.

For decades, successful sports teams have emulated the analytical practices and procedures of top performing enterprises for rewarding fans (e.g. customers) and using ticket pricing practices which have been used by the airline and hotel industry. But now sporting analytical methods have reached a level of sophistication that enterprises can now examine and in turn learn from successful analytical sporting teams such as the All Blacks rugby team, the Boston Red Sox and Baltimore ravens. The growing alacrity by enterprises to learn more is evidenced by the growing success of annual sporting conferences such as the MIT Sloan sport analytics conference has seen attendance by enterprise corporate representatives increase dramatically.

Sports	P&G

Focus on the human dimension – individual and team performance

Sports	P&G
- Players are teams most important and expensive resources - Measure individual game level performance - Measure performance in context – how a team performs with or without an individual player, team performance as a whole in specific games against certain opponents.	- P&G identified that enterprises do not always share similar sentiments pertaining to focusing on the human dimension. They instead focus on operational or marketing issues. - P&G observed that there is also less focus on the human dimension of performance. Some enterprises use human resource analytics but these are not as sophisticated as sports measurements and have only been applied to individuals. - P&G evaluate across different team compositions for various customers to identify star players "(+/-) players"

Work within a broader ecosystem but build close relationships with key analytic experts.

Sports	P&G
- Sports teams are small businesses so they operate in a broad ecosystem of data, software and service providers. - They key to these partnerships is that they draw as much value from each partner whilst maintaining internal capabilities. - Ideas shared between competitor's means that there is a trade-off between the benefits of adoption among competitors and gaining competitive advantage through excluding early adoption.	- Operating in a broader context is also important for large and SME businesses. · Enterprises are inundated with a never-ending stream of data, technologies and analytics to exploit. - P&G have built close relationships with several vendors of software and data analytics. - They have co-developed business sphere rooms for reviewing and acting on data analyses - They disseminate their niche analytics approach to other large companies at an annual conference.

Support Analytical Amateurs - Individuals analysing their own analytic data to improve measurements

Sports	P&G
- Sports teams provide their individual players with team and personalized analytics and statistics with the aim of improving their performance.	- P&G use comprehension and evaluation models with measurement along particulate criteria. - They motivated employees could keep track of their own performance in order improve their performance. For example, sales employees could use the extensive data from CRM applications to assess and improve their performance.

Table 3.3 Adapted from Davenport [2014]

3.6   Gamification

The gamification concept is rapidly growing in popularity among practitioners, business professionals and academics alike. 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].

From practitioner and business professional perspectives, recent advancements in cloud, location-based and social technologies in addition to the maturation of augmented and virtual reality technologies has meant that gamification is now prevalent across many industries (e.g. health care, education, software development, sports, entertainment etc.). Furthermore, 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].
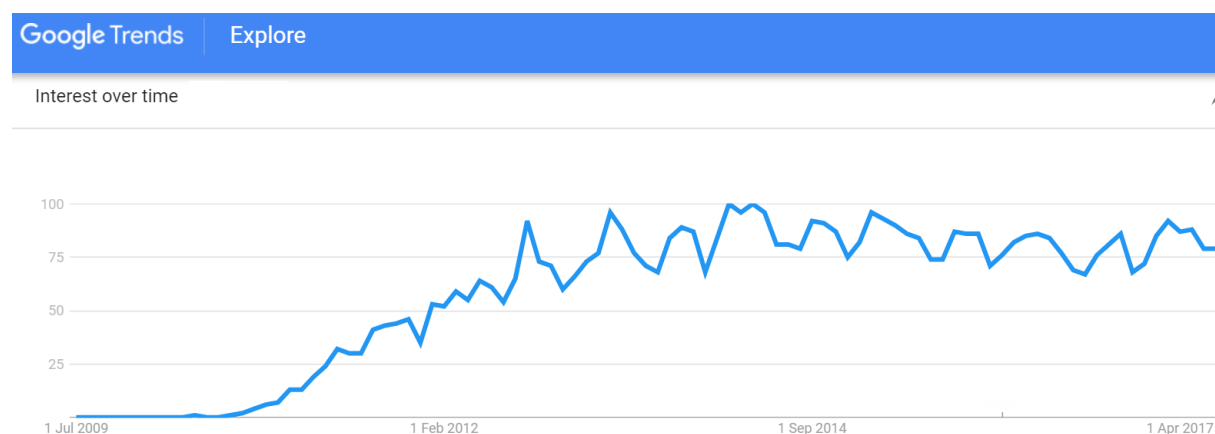

Figure 3.2 Gamification interest from 2009 – 2017

The emergence of the term 'gamification' can be traced back to the digital media industry in 2009 but only entered widespread usage in 2010 (Figure 3.2). However, underpinning concepts date back to over thirty years ago when Malone produced three seminal IS articles which employed terms such as 'intrinsically motivating' software and

'enjoyable user interfaces' which drew heavily from academic literature in fields as diverse as psychology, philosophy, cognitive science and gaming theory [Huotari and Hamari, 2012].

Conceptually, gamification has engendered many diverse and collectively incohesive views concerning its' constitutive properties [Seaborn and Fels, 2015; Hamari et al., 2014]. For example, Seaborn and Fels [2015] further point out that 'few frameworks outlining theoretical foundations and how gamification systems can be analysed exist'. Following a comprehensive survey of the literature, we have identified a number of core game design elements which underpin the gamification concept (Table 3.4) whereby leveraging game design elements, gamification is currently being used in non-game contexts to enhance products and services 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]. Huotari and Hamari [2012] perspective clarifies the outcomes of gamification as "affordances for gameful experiences to support user's overall value creation". These specific game design elements have been conceptualized in a framework developed by Bui et al., [2015] who point out that to improve the previous conceptualizations of gamification, it was necessary to develop their own framework as they found that 'researchers use terms inconsistently or inappropriately'. Mechanics are the primary building blocks of gamification which can be manipulated by game designers to create challenges for players. Examples include user expertise badges and visual bars for tracking player progress. Dynamics or user-system interactions can be dramatically impacted by mechanics. Competition with others and individual challenges are examples of dynamics. Closely linked to the dynamics is the concept of user characteristics which encompasses individual users bring a variety of backgrounds, personalities and experiences to a gamified product or service. Having a comprehensive understanding of user characteristics is essential to ensuring effective gamification. Aesthetics represent design features such as audio, fantasy elements and visuals. The emotionally appealing nature of aesthetics can have a significant impact on dynamics. Finally, motives refer to two specific outcomes: immediate and long-term. Immediate outcomes encompass the user deriving a hedonic or utilitarian experience (e.g. engagement, enjoyment, flow from a gamified product/service. Long-term outcomes are the ultimate goals of gamification whereby users engage in performance and/or behavior modification. However, implementing effective gamification techniques is challenging with

Gartner [2014] predicting that 80% of gamifications projects will fail because of the incorrect operationalization of game design elements. For instance, gamification comprises the design and operation of gamified service bundles for the implementation of transformed and newly created business processes. This includes the design of technology-based, gamified enhancing services in conjunction with the adaption of central offers so that both parts can be bundled. Embedding electronic sensors in Nike sports shoes was a pivotal pre-requisite for creating the globally successful gamified Nike+ service bundle. Thus, "the design and adjustment of gamified service bundles is a complex task that exceeds applying simple point systems and badges" [Blohm and Leimeister, 2013].

Game Design Elements	Source
Mechanics	Blohm & Leimeister (2013), Bui et al. (2015), Deterding et al. (2011), Hunicke et al. (2004), Ralph & Monu (2014), Zichermann and Linder (2011)
Dynamics	Blohm & Leimeister (2013), Bui et al. (2015), Hunicke et al. (2004), Ralph & Monu (2014)
Motives	Bui et al. (2015), Blohm & Leimeister (2013), Koivisto & Hamari (2014), Malone (1981)
Aesthetics	Bui et al. (2015), Deterding et al. (2011), Hunicke et al. (2004), Ralph & Monu (2014)
Characteristics	Bui et al. (2015), Malone (1981), Morford et al. (2014)

Table 3.4 Existing Gamification Framework Components

Gamification is currently being used for self-tracking and self-surveillance purposes and aligns itself well to personal analytics applications. For instance, the use of mobile health (mHealth) applications for incentivizing health behaviour change continues to grow at an unprecedented rate. 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, and Fuelband, have become increasingly popular with an estimated 25 million fitness applications sold in 2015 [GFK, 2015]. However, for these applications to be truly effective they require the user to be wholly comfortable and transparent with the levels of personal data which are entered and subsequently generated by these devices. For instance, most of these fitness applications monitor heart rate, chart sleep patterns, log exercise, diet and calories, enable social media sharing and compare users to their peers to set goals. Consequently, the manufacturers of

these mHealth applications often use specific gamification techniques not only to dilute these fears but to also incentivize repeated use of these devices.

3.7   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 et al., 2017b]. 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]. While there are many definitions of cloud computing, one of the most widely used is provided by the National Institute of Standards and Technologies (NIST) who characterize cloud computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (for example, networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or IT service provider interaction" [Mell and Grance, 2011]. Further, this description is specific in detailing cloud computing as comprising five essential characteristics, four deployment models, and three service offerings. This conceptualization serves as a "means for broad comparisons of cloud services and deployment strategies….and provides a baseline for discussion from what is cloud computing to how to best use cloud computing" [Mell and Grance, 2011].

Clohessy et al., [2013] have conceptualized this definition as a 5-4-3 model of cloud computing (Figure 3.3). Looking upward in the model, the base layer has 5 components. These are essentially attributes that form the basic tenets of cloud-based computing. The first of these, broad network access, encompasses end user and device-based access to remote servers situating cloud services or applications, and describes access to computing resources over networks, whether intranets or public internet, using thick or thin client devices and multiple platforms including laptops, tablet PCs, smart phones, and new emerging computing devices. Essentially, this component assumes that end users can connect to remote servers. The second, rapid elasticity, describes a cloud service provider managing a user's resource utilization based on evolving needs, with a cloud service deterministically scaling up or down to meet user needs. The third, on-demand self-service, describes a requirement from end

users for ubiquitous computing capabilities such as storage or processing power at any time, without the requirement for human interaction with the service provider. The fourth, measured service, represents the provision of user-based resource consumption metering by cloud service providers. Lastly, resource pooling, represents the provision, using multi-tenant models, of pooled computing resources to multiple consumers, where physical and/or virtual computing resources are a shared resource, in essentially a one-to-many provisioning relationship.
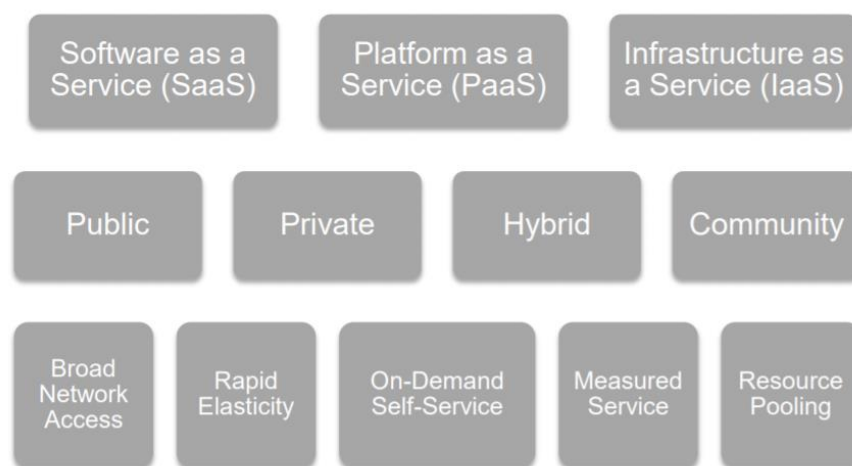
Figure 3.3 5-4-3 Cloud Computing Model [Clohessy et al., 2013]

The middle layer in Figure 3.3 describes the types of cloud. When cloud computing services are offered in a 'pay-as-you go' manner to the public it is referred to as a public cloud. Examples include Microsoft Azure Services and Amazon Elastic Compute Cloud (EC2). The service is sometimes termed utility computing. The technologies underpinning public clouds reside on the premises of the cloud provider. A private cloud, typically provisioned for exclusive use by a single organization and use of cloud applications that are not made available to the public. Unknown parties do not share resources. The cloud may be managed by the organization or by a third party. Amazon's Elastic Compute Cloud (EC2) also offers private cloud services. A community cloud extends a private cloud, provisioned for specific use by a community of organizations or users for shared purposes, for example, security or legal compliance. A hybrid cloud comprises some combination or variant of the previous models. The innovative value of these various types of cloud lies in a trade-off between costs and overall control. The top layer in Figure 3.3 describes cloud computing's well-established service models, differentiated into three distinct categories depending on the capability provided, and referred to as the SPI (Software, Platform, Infrastructure) model.

The first of these three, Software as a Service (SaaS), describes a computing scenario where the cloud provider allocates the user with software resources and capabilities, delivered through the user's web browser or thin client download, eliminating the need for the user to install or manage complex software or acquire additional hardware. The second component in this layer describes service provisioning of computing platforms, Platform as a Service (PaaS). Here the cloud provider allocates the end user with a complete computing environment, typically for software development or application testing through provision of developer tools, database management, or testing functionality. The end user may deploy created or acquired applications onto the cloud. An example of PaaS is IBM's Bluemix. The third and last component in this service layer is Infrastructure as a Service (IaaS), where the cloud provider allocates storage and computing resources to an end user, through the provision of (multi-)server storage or processing, or virtualization of computing infrastructures. It represents the outsourcing of a complete computing infrastructure. This conceptualization of the cloud computing concept has been recently extended to encompass a new dimension known as the personal cloud.

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 online photos storing platform 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. According to Kleynhans [2015] the personal cloud is growing in importance as "it shapes how employees operate across their digital lives whereby digital workplace managers responsible for building the digital workplace will be increasingly challenged as the personal cloud continues to evolve and intersect with IT initiatives". Gartner have predicted that by 2018, 25% of large enterprises will have an explicit strategy to transform their existing corporate computing environment experience into a consumer like computing experience [Gartner, 2015].

3.8   Neuro Information Systems

The use of neurophysiological tools have received much attention in the social sciences in recent years due to their ability to complement existing sources of data captured directly from the human body [Lieberman 2007]. For example, researchers in the emerging field of neuro information systems (NeuroIS) have used neurophysiological and neuroimaging (e.g. fMRI) tools to measure how people react to various IT stimuli such as security messages [Jenkins et al. 2016], instant messaging (Minas et al. 2014), video games [Turel et al. 2016} and systems breakdown [Riedl et al. 2012]. The primary advantage of neurophysiological tools is the ability to measure actual biological responses to certain stimuli, which often a person is unaware of. As famously stated by marketer David Oglivy, the trouble with asking people how a new product makes them feel, is that people don't think how they feel, they don't say what they think, and they don't do what they say. When studying the impact of systems breakdown on computer users, Riedl et al. [2012] found increases in the stress hormone cortisol even though users reported no feelings of stress. For this reason, neurophysiological tools are particularly well equipped for measuring constructs people are unable to accurately self-report, such as cognitive overload or the emotions and habits associated with systems use [Dimoka et al. 2012]. But that does not mean neurophysiological tools are better than traditional self-reported methods. As neurophysiological data cannot be manipulated by the subject, or susceptible to social desirability bias, triangulation with additional data sources can result in a more holistic representation of research constructs [Tams et al. 2013; Dimoka et al. 2012]. Thus, combining neurophysiological data with self-reported surveys and semi-structured interviews will prove fruitful for IS researchers.

Yet, few IS researchers have considered how neurophysiological tools can enhance their studies, largely due to the costs of heavyweight technologies involved, such as fMRI, and the deep associated knowledge required to measure and respond to biological influences. Table 3.5 details the traditional tools used in NeuroIS research and the approximate costs. However, the cost, operational complexity, and intrusiveness, of NeuroIS tools are falling rapidly. In parallel, the accuracy of such lightweight devices is constantly improving and in some cases is on a par with the heavyweight counterparts. For example, Ofir et al. [2016] used Fitbit devices to investigate the link between video game addictions, sleep duration, and obesity. To validate the accuracy of the Fitbit in measuring sleep duration, Ofir and colleagues compared the Fitbit, which costs between $60 and $150, to polysomnography (see Table 3.5 for description), considered the gold standard for objective sleep measurement.

Sleep duration measured by the Fitbit highly correlated with sleep duration measured by polysomnography, validating its use for future IS studies.

	Focus of Measurement	Cost (USD$)
Psychophysiological Tools		
Eye Tracking	Eye pupil location ("gaze") and movement	~$10,000 or ~$100/hour
Skin Conductance Response (SCR)	Sweat in eccrine glands of the palms or feet	~$2,000 or ~$25/hour
Facial Electromyography (fEMG)	Electrical impulses caused by muscle fibers	~$3,000 or ~$40/hour
Electrocardiogram (EKG)	Electrical activity of the heart on the skin	~$5,000 or ~$50/hour
Polysomnography	Brain waves, blood oxygen levels, heart rate and breathing, as well as eye and leg movements during the sleep.	~$1,000 - $5,000 per study
Brain Imaging Tools		
Functional Magnetic Resonance Imaging (fMRI)	Neural activity by changes in blood flow	~$200-500/hour
Positron Emission Tomography (PET)	Metabolic activity by radioactive isotopes	~$200-500/hour
Electroencephalography (EEG)	Electrical brain activity on the scalp	~$100-200/hour
Magnetoencephalography (MEG)	Changes in magnetic fields by brain activity	~$200-400/hour

Table 3.5 Typical NeuroIS tools and approximate costs (Adapted from Dimoka et al. 2012).

In addition, wearable NeuroIS devices enhance ecological validity as the IS researcher is able to gather biological data from natural settings. The findings from studies employing wearable NeuroIS devices can be generalized to the situations facing a wide variety of IS users, thus enabling more effective solutions to contemporary problems such as technology overload [Karr-Wisniewski & Lu 2010], technostress [Tarafdar et al. 2007], and deviant IS behaviours [Turel & Qahri-Saremi 2016]. In contrast, due to the size and complexity of most neurophysiological tools, studies tend to be conducted in artificial settings, such as tightly controlled lab experiments, which are often not generalizable to the real world [Levitt & List 2007].

The use of wearable neurophysiological devices in scientific studies is still quite novel. It is only possible to conduct such studies now as wearable neurophysiological tools have just reached a point in their development (due to miniaturization and increased battery life) where their invasiveness, portability, and accuracy is harmonious with actual workplace settings. In addition to the Fitbit, other wearable devices have enabled researchers to advance our understanding of certain phenomenon. For example, the Empatica E4 wristband (see Figure 3.4) has recently been used to automatically detect ongoing motor seizures through SCR in epilepsy patients [Regalia et al. 2015] while the Tobii Pro glasses have been used to measure cognitive overload in physicians [Szulewski et al. 2015]. Stress is a phenomenon that has attracted much interest from the IS community. Measurement of cortisol within the body is the most widely accepted single measure of stress, but detecting cortisol levels involves saliva testing which is not practical in everyday life. For in-situ and unobtrusive measurement, heart rate variability and SCR are proven very useful psychophysiological markers for detecting changes in stress.[Riedl & Léger 2016]. Such measures can now be detected with consumer smartwatches and fitness trackers, some of which specialize specifically in stress detection (e.g. the Microsoft Band and the Garmin vívosmart 3).
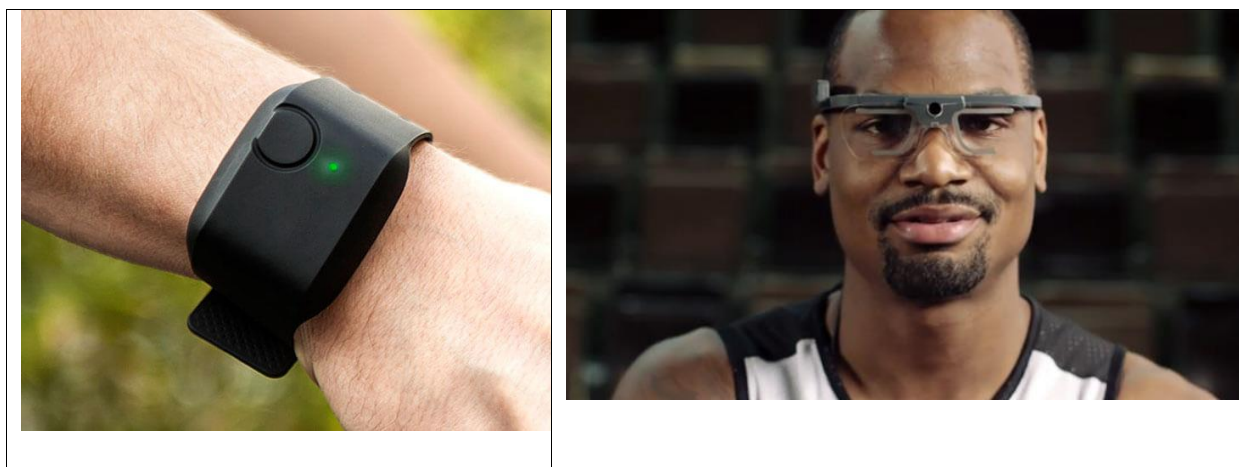

Figure 3.4 Wearable neurophysiological devices; Empatica E4 wristband and the Tobii Pro Glasses

Further reducing the complexities of gathering and analyzing neurophysiological data, companies such as Google and Microsoft now offer cloud-based emotion detection API's. Through Microsoft's Emotion API for example, facial expressions from video or images can be analyzed to detect anger, contempt, disgust, fear, happiness, neutral, sadness, and surprise. These emotions are associated with particular facial expressions that apply across cultures. Using the camera functions embedded in almost every smartphone, laptop and PC, researchers can outsource data to public API's to answer pertinent IS questions such as 'What emotional reactions does a new software system engender in users? or 'What particular

software features are associated with stress or enjoyment?' Indeed, emotion detection API's are not limited to facial expressions. Emotions can also be detected from a user's voice (see www.beyondverbal.com), eye movement (see https://webgazer.cs.brown.edu/), mouse movement (see https://neuro-id.com/), and written text (see https://www.ibm.com/watson/services/tone-analyzer/). There are a number of neurophysiological measurement tools available, all with their own advantages and limitations. The selection of neurophysiological tool is critically important to the success of a study as the decision has consequences for reliability, validity, sensitivity, diagnosticity, objectivity, and intrusiveness [Shitkova et al. 2015]. To select the most suitable neurophysiological tools for the study at hand, IS researchers are advised follow the 'NeuroIS tool selection framework' developed by [Shitlova et al. 2015].

3.9   Summary

In this Chapter, we discussed how the individuation of IS and advances in analytical and business intelligence technologies have resulted in the emergence of seven personal analytics trends which traverse multiple disciplines such as learning analytics, the quantified self, human-centric personal analytics, gamification, sports analytics, personal cloud and NeuroIS. These trends are currently shaping the personal analytics landscape. As highlighted by specific examples in this chapter, it is inevitable that the use of personal analytics technologies within an enterprise setting will become mainstream in the coming years. This increased application of intelligence to employee personal information to enhance specific outcomes (e.g. enhance user experience) will create both challenges and opportunities for organizations. For instance, the increased use of sophisticated mobile technology devices by employees resulted in organizations having to create bring-your-own-device (BYOD) policies. In a similar vein, organizations are increasingly having to create wear-your-own-device (WYOD) policies to control and monitor the use of these devices within the workplace. Consequently, in the next chapter we introduce the concept of 'enterprise personal analytics' which we believe will represent the next evolution/frontier of the personal analytics concept. We also present a framework, derived from a survey of the personal analytics literature, which consists of various combinations of stakeholder perspectives and concerns. This framework can be used to guide and coalesce future research on the concept of enterprise personal analytics.

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Enterprise Personal Analytics: Research Perspectives and Concerns

In Chapter 3, we presented an overview of seven specific personal analytics concepts which are inspiring enterprises to consider the use of personal analytics within their organizations. In this Chapter, we introduce the concept of enterprise personal analytics (EPA), a term which we have coined to reflect a new business analytical phenomenon which we envisage will reinvent how enterprises source analyse and use employee personal data. To date, the mainstream application of personal analytics in an organizational setting remains relatively niche. According to Gartner, it may take between 5-10 years for the adoption of personal analytics technologies to become mainstream [Ingelbrecht and Herschel, 2015]. However, like many IS researchers [e.g. Davenport, 2014; Lee and Balan, 2014; Clohessy and Acton, 2017a] and IT analysts [e.g. Ingelbrecht and Herschel, 2015; Kleynhans, 2015] we believe that the emerging concept of EPA has the potential to become the new frontier of competitive differentiation. However, there is currently a dearth of IS research frameworks which can guide future research on this topic [Baskerville, 2011; Clohessy and Acton, 2017b]. Consequently, we present a two-dimensional grid (stakeholders and perspectives) research framework which can be used to guide and bound future research in EPA.

4.1 Introducing Enterprise Personal Analytics

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 EPA 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 Chapter 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]. To leverage these benefits enterprises are responding to IT consumerization by introducing a number of proactive personal analytics strategies. For instance, enterprises are using employee's personal analytics 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 IS and business intelligence research exists on how on enterprises and their workers can simultaneously and harmoniously leverage the benefits of EPA data. This is understandable given the embryonic nature of the personal analytics concept, specifically in the context of an enterprise setting. Additionally, as discussed in Chapter 3, it has been claimed that the IS discipline have largely benighted the individuation of IS [see Baskerville, 2011; Huang et al., 2015] and the digitization 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. However, there is significant potential, from both organizational and individual worker perspectives, for the use of EPA, but much research is needed for the concept to realise its full potential. While several authors have proposed research frameworks for EPA [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 (see Chapter 2), we have derived a two-dimensional grid (e.g., research perspectives and concerns) framework which can be used to guide future empirical investigation (Table 4.1).

Table 4.1 EPA Two-Dimensional Grid Framework: (A) a multi-concern, single perspective study, (B) a single-concern, multi perspective study, (C) a single-concern, single perspective study

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 (Chapter 2) we identified five specific *concerns* pertaining to the use of personal analytics in an enterprise setting which we discuss in section 4.3. These concerns are depicted as one dimension of our research framework. As EPA involves multiple stakeholders it is useful to study the concept from different *perspectives*. Our analysis revealed several perspectives namely that of companies, workers and the mode through which companies enable workers to use personal analytics (e.g. modality). These three perspectives, which are outlined in section 6.2, represent the second dimension of our research framework. In Chapter 5, we discuss the theoretical implications of our research (section 5.1). To assist with future research, we have populated the two-dimensional grid with sample research questions which we argue merit further scrutiny in an EPA context. Furthermore, in Chapter 5, we delineate the practical implications of our research (section 5.2). To this end, we have also devised a visual mapping artefact which we have coined as the "enterprise personal analytics metro map" which could be used by companies to plan and map their EPA digital transformation initiatives.

4.2   Enterprise Personal Analytics Perspectives

4.2.1   Company

This perspective represents forward-looking organizations who are looking to adapt to EPA and the consequent complexity inherent to this migration and how personal analytics is enabling individual and team work while minimising risk to their business. Modern 21st-century workplaces are increasingly becoming more transparent, instrumented and more data driven. As a result of the personal analytics trends discussed in Chapter 3, companies are orientating their organizations towards the development of tools which are capable of monitoring, tracking and enabling a better understanding of their worker's activities. Organizations can have different motivations for using EPA. 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. For example, organizations can derive value from employees who use their personal analytic devices to productively sync to organizational resources while working remotely (e.g. smart watches). There is also scope for organizations to use personal analytics in a team context so that they can evaluate across different team 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 perform with or without a particular worker. This is called "plus/minus" analysis.

We will now discuss two specific EPA technologies which are increasingly being adopted by organizations in terms of wearable fitness and employee social engagement tracking devices. With regards to wearable fitness devices, a study conducted by ABI research [2013] highlights how more than 13 million wearable fitness tracking devices are expected to be incorporated into employee wellness programs by organizations over the coming years. Increasing healthcare costs and the increased use of health insurance premium cost reduction

incentivization measures by healthcare providers are driving the use of wearable and embedded personal analytics technologies within organizations. While basic wearable fitness tracking devices can monitor exercise patterns, calories consumed and the number of hours slept, next generation fitness tracking devices will feature more intuitive and hybrid user designs, enhanced battery life and be capable of measuring hydration and blood sugar levels. In addition to reducing to reducing individual worker health insurance costs, organizations are expected to additional derive benefits in terms of improved productivity and a healthier company culture. This phenomenon has also been bolstered by the passing of the Affordable Care Act, which came into effect in 2014, which allows employers to offer wellness incentives of ranging from 30% to 50% of the total cost of health care insurance. Companies such as BP P.L.C., Barclays, Bank of America, IBM, Time Warner and Target have implemented wellness programmes which are underpinned by FitBit tracking devices. IBM for example provided Fitbit devices to 40,000 employees over a two-year period which saw 96% of the users routinely monitoring health data [Farr, 2016]. Employees who participated in the program obtained an average of 8,800 steps per day in comparison to employees who didn't participate in the programme. However, initial wellness programmes business use cases have reported issues relating to worker privacy invasion concerns, incorrect gamification techniques and the shifting priorities for wellness programmes. For instance, with regards to the latter, there is evidence to suggest that wellness programmes which were underpinned by motives which extended beyond reducing costs (e.g. build a healthier workforce culture) were far more effective as they offered more intrinsic worker rewards [Taylor, 2016]. Moreover, some organizations have attempted to 'gamifiy' their well programmes with leader boards which have served to lionize the fit while concurrently demoralizing those who have underlying health issues [Farr, 2016]. In order to assuage employers' and workers' fears pertaining to the privacy and security of individual employee health care information, vendor companies such as Fitbit have acquired compliance with the U.S. Health Insurance Portability and Accountability Act (HIPPA). The continued and successful adoption of wearable fitness tracking devices within organizations will be dependent on the effective restructuring and transformation of traditional healthcare value chains with wearable fitness tracking vendors forming new partnerships with health care providers, health insurers and corporate enterprises.

The manner with which information, knowledge and expertise is now being shared amongst organizational networks and employees are rapidly changing. As companies become agile, flatter and more collaborative they can no longer rely on traditional formal enterprise structures

to leverage insights from their workforce. Instead, organizations are attempting to leverage their enterprise networks via the use of business analytical tools. One such tool is IBM's social engagement dashboards which comprise personal analytics key performance indicators to incentivize employees to engage in collaboration activities within the company. These personal dashboards use big data which is captured either by IBM's collaboration tool called connections to by third party employee social network analytics platforms. Each employee is provided with a real-time scorecard which enables them to better understand their role within a specific network and how to increase their impact through knowledge, reputation, network and social capital. Having access to macro and granular levels of real time feedback information motivates employees to engage with projects/initiatives on a sustained and continued basis. The applications for technologies such as this are most likely to be used in innovation projects, particularly with regards to emerging inner source innovation initiatives. Inner source encompasses the use of internal networks to foster collaboration and the sharing of knowledge, skills and expertise within a company.

However, in most organizations, "analytics efforts 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]. While the forward looking organizational trend towards the technologically enabled surveillance of employees is expected to lead to better hiring, improved workplace conditions, healthier and more productive employees and better management, organizations will have to take into account a number of salient considerations which a company must take into account prior to commencing an EPA digital transformation journey such as: identifying the maturity and sophistication of the organization's analytical capabilities, determining the turnaround time for implementing such a strategy (e.g. quick wins vs longer-term goals), implementing procedures for gaining strong organizational commitment towards the new personal analytics strategy and most significantly the impact on individual worker morale and group team dynamics.

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 with regards to an 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 valuable tools in attracting and retaining these new hires" [Harris et al., 2012]. Furthermore, in lieu of the recent trends discussed in Chapter 3, workers have become increasingly comfortable with sharing their individual metrics as a means of enhancing their productivity [Smarr, 2012; Dobrinevski, 2013].

How companies organize 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 EPA context. Traditional EPA '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]. Consequently, there are many open questions that would be of great interest. Some initial work has been done on how companies can organize 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 organize EPA efforts within the organization at an individual worker level and assistance with the core analytics processes which would be required to support this [Grossman and Siegel, 2014]. For instance, while the user experience of activity tracking applications (e.g. Fitbit, Nike+) comprise elements which intrinsically motivate users (e.g. automated coaching, social comparison) to share their personal data in to receive accurate feedback, EPA tools and dashboards have yet to achieve this level of acceptance.

Organizations must determine how they can implement personal analytical strategies which mimic the benefits of personal activity applications providers derive in terms of loyalty, brand engagement and real user data activity monitoring. In return, users derive a multifold of self-improvement benefits. This model which has been tried and tested has potential to be used

within an enterprise setting. If these personal analytics technologies can be used to motivate people to achieve specific goals in their personal lives (e.g. run faster, lose weight), questions arise pertaining to if they can be used to achieve similar goals in people working lives? For example, can EPA technologies be used to motivate customer support workers to increase the number of satisfied customers they have following each interaction or can they be used to assist sales representatives enhance their sales pipelines? With regards to the latter, Davenport [2014] describes how organizations are moving towards the provision of relevant data analytics dashboards, traditionally used by managers, to employees. He describes a scenario where a company enables their sales employees to use the extensive data from their customer relationship management applications to assess and improve their performance. For instance, if 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. Another obvious avenue where EPA can be of mutual benefit for the company and the worker encompasses human resource management. According to a survey conducted by Korn Ferry [2017] 10 and 25 percent of new hires leave within 6 months of starting their position with most them reporting that they were not fully engaged with their tasks and responsibilities. The reasoning for this has been pointed towards ineffective and antiquated methods of hiring employees (e.g. intuition, computerized tests, obsolete rules of thumb). These traditional human resource metrics and methods are overly simplistic and rely on retrospective analysis. EPA metrics may offer superior personal insights by enabling organizations to hire, evaluate and reward employees based on the real-time analysis of past, present and future trends and patterns. While the concept of talent assessment is not new, digital technologies have evolved to a level of sophistication (e.g. cloud computing, big data, business intelligence tools) which allows for a more accurate and in-depth measurement of current employees and potential new hires. For example, the global talent management company Korn Ferry have incorporated simulations which are underpinned by algorithms to find the best of breed talent. When a new potential new hire impresses at the interview stage they must them complete a simulation exercise against a rival candidate. The candidate which performs best at the simulation exercise is then offered the position. The American retailer Sears, who hire between 140,000 to 160,000 retail sales representatives a year, has also implemented a retail technology simulation to assist them with the hiring process. Potential hires must initially fill out an application form and then complete an interactive video game where they encounter real type sale scenarios and navigate through a multitude of customer based situations. As part of the process, the candidates become members of the Sears loyalty program so even if they are not hired they become Sear's

customers. Currently, Google's human resource function entitled 'people operations' is an exemplar human talent management system which is responsible for ensuring that on average every employee generates $1 million in revenues and $200,000 in profits on an annual basis. Their talent management system is underpinned by unique personal analytics data which measures leadership, ownership, humility and cognitive ability dimensions. Implementing EPA strategies within a company, however, may not be a panacea for all organizational talent management issues. There is a risk that enterprises view personal data in a vacuum and may become over reliant on metrics and lose sight of the 'human element'.

According to Gartner, workers are beginning to reap the benefits of new consumerized working environments which are underpinned by digital transformation personal analytics initiatives [Ingelbrecht and Herschel, 2015]. This phenomenon is likely to continue because of employee driven consumer technology and usage trends and the proactive efforts of organizations who want to exploit these consumerization trends as a means of enhancing employee engagement and achieving enterprise objectives across a range of domains.

4.2.3 The 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 an expanding set of information, services and devices such as traditional computing and communication (platform, desktop, mobile, tablet), wearable (health monitors, augmented and virtual reality displays), internet of things (mobile apps, consumer appliances, transportation and environmental sensors), and data storage (hard drives, cloud, USB) are fluidly and dynamically interconnected to support intelligent digital ecosystems. This continuously expanding digital ecosystem, which is has been coined as an "intelligent digital mesh" [Clearley, Walker and Burke, 2015], is evolving around the individual (figure 4.1). This interconnected digital mesh, which blurs the lines between the physical and virtual digital worlds, requires organizations to consider the impact of adopting potentially disruptive EPA tools and devices on their extant business processes, employees and digital systems. Most significantly, enterprises must evaluate how they can optimally design EPA solutions and user experiences while concurrently tackling the problems they create. For instance, all the devices and services depicted in figure 4.1 can produce and communicating an endless and often unmeasured amount of data (e.g. sensory, unstructured, contextual). An organization's ability to effectively leverage this confluence of these data sources is dependent on the way they

design their individual system architectures. We will discuss this concept and priority concern in greater depth concern in section 4.3.1.
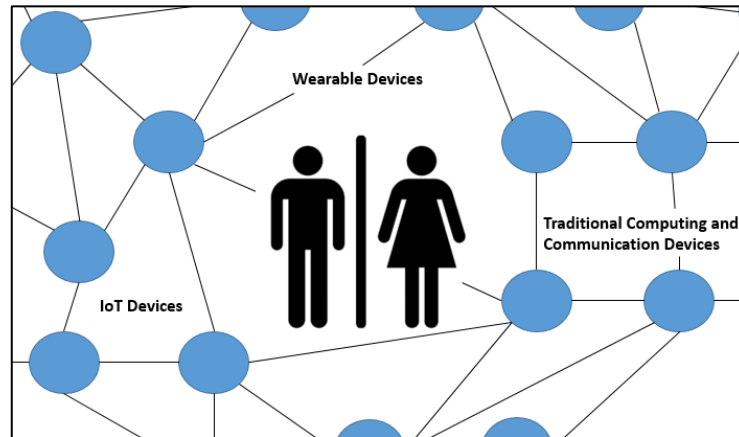

Figure 4.1 The Digital Mesh adapted from Clearley, Walker and Burke, (2015).

As our digital environment 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. multitasking, context switching) effectively is a salient requirement for the successful development of a company's EPA strategy. A digitally saturated working environment can create a number of salient challenges for organizations. For instance, workers can experience communication overload as a result of their continuous interactions with a multitude internal communication ICT channels. This can lead to issues relating to an employee's deterioration in cognitive control, attention span and a loss of productivity and quality of life [Whelan, Islam and Brooks, 2017]. Such is the seriousness of the problem; global governments are introducing specific legislation to combat the problem. For example, in the case of workplace emails, in 2016 the French government passed a new El Khomri "the right to disconnect" law which made it illegal for employers to contact workers via email outside of designated working hours. Similar in 2014, German car manufacturers Volkswagen and Daimler (on a voluntary basis) agreed to stop the sending of emails to their workers outside of normal office hours. The positive impact for both companies has been significant. Particularly in the case of Volkswagen who introduced a "no bypass" safe guard mechanism for employees who were tempted to 'check in' and review their emails.

Employee interactions with enterprise social media collaboration endpoints such as Yammer, Slack and Google docs have also been cited as antecedents to communication overload [see Whelan et al., 2017]. The ubiquitous nature of these services makes them ripe for overuse given that they can be accessed via mobile devices. Furthermore, the nefarious impacts of technology enabled addiction should not be taken lightly. Research conducted by Alter [2017] highlights how social technologies are engineered to encourage harmful behavioural addiction amongst users (e.g. constantly checking your mobile phone). In an EPA context, this phenomenon of information overload and addictive behaviour may become even more pronounced if not planned for or managed correctly by an enterprise. Therefore, when considering the best modalities for their EPA initiatives, organizations should consider the frequency of interruptions and how quickly users can recover from them. Clearly delineated policies should also be put in place so that employees are not left second guessing what is expected of them when using EPA devices. Without clearly defined protocols in place, workers run the risk of drowning in an never-ending stream of information.

4.3   Enterprise Personal Analytics Concerns

4.3.1   Individual Information Systems Architecture

Advances in information and communication technologies (ICT) over the last 20 years has "enabled more-and-more complex individual IS" (Baskerville, 2011). 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 [Harris et al., 2012]. Organizational users differ from private users, or consumers in important ways. For instance, when compared with private users whose motivations are dependent on social and private contexts, organizational users are not free to choose their activities, IS or technologies whose use by organizations is largely driven by economic conditions [Spottke, Eck and Wulf, 2016]. However, academic research has no "conceptual way to describe and examine this collection of technologies that an individual assembles to support themselves in their work and private life" [Carroll and Reich, 2017]. Consequently, recent IS research studies have called for an expanded investigation into the individuation of IS [Yoo, 2010; Baskerville, 2011 and Carroll and Reich, 2017] whereby the 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]. For example, research efforts

have used portfolio theory [Carroll and Reich, 2017] and the concept of individual information systems architecture (Baskerville, 2011) to shed light on the phenomenon. With regards to portfolio theory, Carroll and Reich, [2017] identified that the individual collections of technology used in people's private and working lives could be usefully called a technology portfolio, defined as "a purposeful collection of technologies that an individual assembles to meet their needs." Furthermore, the authors identified five specific technology portfolio life cycle stages: scan, research, trial, use and retire. While these stages resemble other assimilation models, the life cycle features two new sub-cycles (e.g. scan and retire) and an innovative in lieu of a rational decision-making process.

A typical individual's information system (IIS) architecture is inherently complex comprising of two specific 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 individually and enterprise provided cloud computing technologies which produce and consume services. Figure 4.2 depicts the IIS architecture of John Doe. Given the opaque nature of IIS, our knowledge relating to how John Doe has designed, planned and controls the architecture depicted in figure 4.2 is limited. Furthermore, questions arise pertaining to why John Doe has made the choices and investments reflected in figure 4.2? Most significantly, questions emerge pertaining to how organizations can optimize John Doe's IIS architecture? We would like to stress that given the current uniqueness of IIS architectures, other examples might be more complex, and others simpler. This is a single example. Baskerville [2011] opines that organizations can no longer ignore IIS architectures for the following reasons. First, IIS represent the most recent frontier for the computer information system design. Second, they IIS complicated and unique systems which cross boundaries between personal life (e.g. social aspects) and work life (e.g. organizational aspects). Third, IIS do not merely store data, individuals are "actively collecting data and processing it into information for various purposes and feeding it outward" [Baskerville, 2011]. The dearth of research into the individuation of IS leads to a number of possible EPA IIS architecture research questions (see Chapter 5).
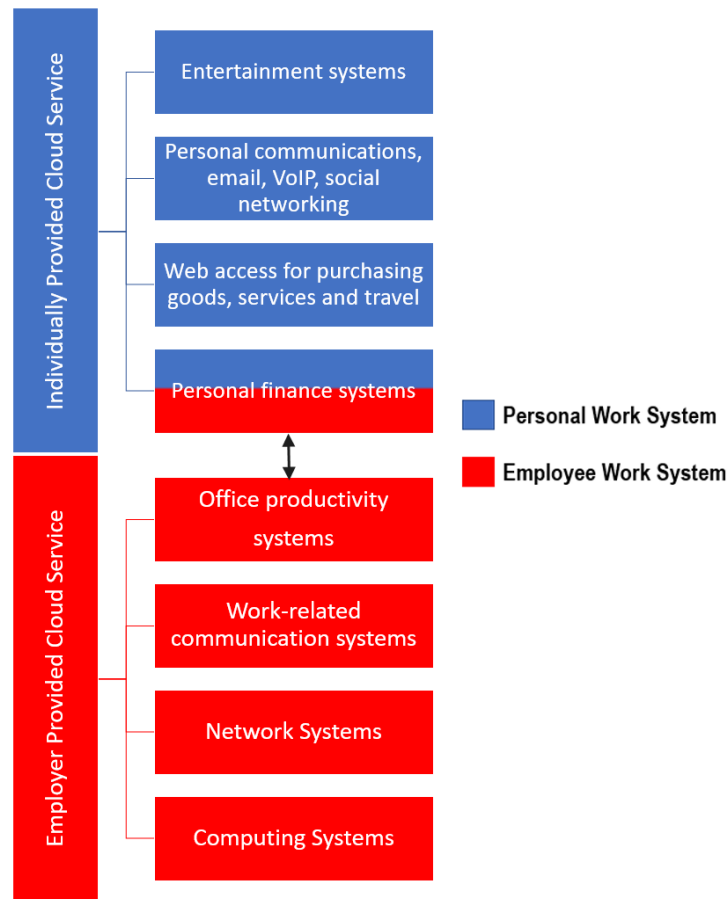
Figure 4.2 John Doe's Individual information system architecture. Adapted from [Baskerville et al., 2011]

4.3.2   Knowledge and Intellectual Property (IP)

The writings of Plato and Aristotle describe how the pursuit of knowledge was an essential ingredient to amassing wisdom. Knowledge is a multi-layered concept which has been defined as both a "justified true belief" [Nonanka, 1994] and a conduit for achieving great power where "the formation of knowledge and in the increase in power reinforce one another" [Foucoult, 1977]. Nonaka [1994] stresses that both knowledge and information are separate entities where knowledge whereby "information is a flow of messages or meanings which might add to, restructure or change knowledge". Nonaka [1994] proposed a theory of organizational knowledge creation which described how "the knowledge held by individuals, and organizations can be simultaneously enlarged and enriched through the spiral, interactive amplification of tacit and explicit knowledge held by individuals and organizations…they key for the synergistic expansion of knowledge the joint creation of knowledge by individuals and organizations". In the last decade, the concept of big data has seen the emergence of terms such as data mining, knowledge discovery and knowledge extraction which are often used

interchangeability in the business analytics domain. However, many practitioners use knowledge discovery as a synonym for data mining and knowledge extraction. Knowledge discovery is defined as the "non-trivial process of identifying, valid, novel, potentially useful, and understandable patterns in data…concerns the entire knowledge extraction process, including how data are stored and accessed, how to interpret and visualise the results and how to model and support the interaction between human and machine" [Cios et al., 2007].

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 value-creating competitive actions" (Sharma et al., 2010). Modern organizational business operations encompass knowledge-intensive management and sharing processes. Subsequently, organizations have turned to business intelligence and analytical applications to manage the day to day running of their business operations. While these applications may have been used in the past to merely produce high-level summarized data about business performance, they are now being used to analyse this data in specific business contexts which can drastically improve decision making and the organizational knowledge cycle. EPA possesses the potential to create a new dimension in the organizational knowledge cycle which organizations can leverage to gain information and insights which can improve business operations and improve decision making. 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 EPA context, where the individual worker personal analytics' data is an information asset, the manner with which knowledge and intellectual property is managed becomes of paramount importance from legal and ethical perspectives.

From a legal perspective questions arise with regards to scenarios where an employee leaves a company, questions arise pertaining to: who owns the individual workers' personal analytics data? The company or the worker? If the answer is the latter, questions arise pertaining to whether workers use their own personal analytics data as a means of highlighting their expertise and skills to prospective employers within their personal curriculum vitae? Moreover, does this transfer of worker personal analytics data make companies more vulnerable to competitors employing collective intelligence techniques (e.g. using competitor

data sources to predict their strategies)? We do acknowledge that there may be irreconcilable conflicts between the company's and employee's interests with regards to EPA. Take for example, cases where organizations make employees sign non-compete/disclosure agreements which could hamper a worker's ability to take their personal data to another job in their current industry.

From an ethical perspective, the increasing use of EPA initiatives raises questions about their impact on worker privacy within the workplace. While the recognition of EPA data itself may not be viewed as an invasion of privacy, the manner with which the data is obtained, measured and used may result in some ethical considerations. Moreover, how the company may use this personal knowledge may generate other troublesome issues. The existence of an on premise or cloud-based enterprise database may be tempting for hackers or third based entities searching for personal data. With regards to the latter, Luppicini [2013] describes how companies that store biometric data which contains "facial-scan or finger-scan data may be tempting to law enforcement agents or private sector companies searching for employee personal data…every biometric database becomes a potential database of criminal records".

Consequently, the (ill)legal and (un)ethical considerations with regards to EPA creates the urgent necessity of safeguarding personal individual information and knowledge. Furthermore, organizations must be sensitive to employees' concerns, which can be alleviated through education and transparency. One possible solution would be for organizations to create BYOD policies which encourage workers (e.g. provide financial support) to purchase and bring their own monitoring devices to work. Such arrangements would see the worker have full control of their own data. For instance, Philips have developed the Rationalizer EmoBowl and EmoBracelets for stock traders. These products are designed to feed data solely to the individual worker (e.g. the primary consumer), without executive involvement, so that they can alter negative working patterns and enhance productivity. Further EPA business cases are required to determine how companies can effectively implement a requisite level of knowledge production versus knowledge protection in an EPA context. Additional research is also required to determine how companies can effectively implement a requisite level of knowledge production versus knowledge protection in an EPA 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].

4.3.3 Motivation and Remuneration

The goal for an organization when designing or introducing a new digital technology or IS is to ensure that workers will want to use it (Markus and Keil, 1994). While the benefits may be clear cut from the company perspective (e.g. enhanced productivity, sales and decision making) getting employees on board can be challenging. Oftentimes, while "there is consensus on the importance of adopting a new digital technology strategy, most employees find the process complex and slow…leaders lack urgency and fail to share a vision for how technology can change the business [Fitzgerald et al., 2014]. 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" [Huang et al., 2015]. For example, "most traditional visualization applications focus on supporting expert analysts with respect to their occupational roles" [Huang et al., 2015]. In a personal analytics context, "employees may investigate 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 analytical tools will need to be accessible" [Mazzei, 2017]. Workers may also be reluctant to share their personal data openly with peers. Particularly, when that data is used to compare their individual performance with others in their team. Furthermore, meaningful individual analysis can only be achieved after an adequate volume of data has been collected. The modality 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].

Ultimately, organizations must develop EPA strategies that inspire long-term use amongst workers. According to Fitzgerald et al., [2014] companies that succeed with the rapid adoption of new technologies by employees "tend to have leaders who share their vision and define a road map, create cross-organizational authority for adoption and reward employees for working towards it…the new technology initiative is viewed as a strategic imperative". Additionally, these companies effectively highlight quick wins, reward early adopters, implement a networking effect (e.g. convince the influencers first), and penalize non-adopters.

For example, in 2017, a company called Three Square Market, became the first US company to offer its employees personal microchip implants, between the forefinger and the thumb, which would enable them to unlock doors, access computers and printers) and pay for vending machine food and drinks. To enhance the adoption of the microchip amongst employees, the company decided not to embed GPS technology into the microchip to alleviate workers fears of being tracked outside working hours. Furthermore, all employees were made fully aware of the benefits (e.g. convenience, replacement of ID badges and credit cards) and the drawbacks (e.g. while FDA approved, they do not come with a no infection/complication guarantee). Because of the company's proactive employee engagement strategy, 50 of the company's 80 employees agreed voluntary to have the microchip implanted. While we do agree that the concept of microchipping employees can be considered extreme, there are lessons to be learned with regards to the manner with which Three Square Market effectively marketed the new personal technology to their employees. Specifically, with regards to alleviating their security and privacy concerns. Other potential uses of the microchip technology include the ability to store a person's passport, travel information, medical history and GPS functionality to safeguard children. The idea of microchipping workers will continue to be a polarizing subject in the years to come.

It is recommended that organizations opt for EPA technologies which are persuasive and come with minimal learning overhead. Persuasive technologies are specifically designed to keep users engaged. For instance, a company called Dopamine Labs are investigating how artificial intelligence can be used to modify mobile applications in a way that alters the user's brain chemistry to repeatedly release dopamine. However, persuasive technologies have recently come under attack from design ethicists who argue that application developers are engaging in a practice of 'brain hacking' through unethical design practices [Williams, 2017]. There is also a grey area pertaining to how continuous self-monitoring of one personal analytics can impact workers. 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]. Furthermore, the use of EPA may lead to unintended behaviours. There is a risk of function creep which is a term used to describe when a EPA technology is used in a different way than its original purpose [Luppicini, 2013]. For example, Function creep may lead to the organizations and management discriminating against specific workers and/or groups because of their individual EPA profiles. This profiling may facilitate

the scapegoating of persons or groups for having or not having certain EPA characteristic or metrics. The lessons learned from the large-scale abandonment of personal health tracking technologies which is currently occurring amongst users of smart watches and fitness trackers can provide valuable insights for organizations contemplating implementing EPA initiatives. [Canhoto and Arp, 2017].

4.3.4 Information Governance

Information governance is the set of multi-disciplinary policies and controls aimed at managing information at an organizational level, supporting legal, regulatory and risk compliance requirements. Effective information governance policies secure confidential data and enable unneeded data to be disposed of in a systematic and legally compliant manner. 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. According to Smallwood [2014] "there is a high-value benefit of basing business analytics decisions on better, cleaner data, which can come about only through rigid, enforced, information governance policies that reduce information glut". Furthermore, effective information governance policies secure confidential data and enable unneeded data to be disposed of in a systematic and legally compliant manner. However, information governance has emerged as a major challenge for organizations in today's environment of big data, business analytics, increasing information risks etc. There are a plethora of high profile examples of how poor information governance practices can lead to disastrous consequences for the organization in question (e.g. US National Security Agency, Ford motor company, Sony). Moreover, ineffective information governance has been cited as a major stumbling in business analytics digital transformation journeys [Lavelle, 2011]. In the case of EPA, 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 EPA 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 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]. In other instances, certain manufacturers of these devices sell on customer information to third parties. Most significantly, the general data protection regulation (GDPR), which comes into regulation in 2018, applies to all companies worldwide that process the personal data of European Union citizens. In an EPA context, the biggest challenges presented by GDPR will encompass the introduction of:

- a broader definition and scope in relation to personal data

- stringent worker consent procedures

- mandatory privacy impact assessments

- the appointment of a data protection officer

- common data breach notifications

- stringent data handling principles (e.g. the right to be forgotten)

- privacy by design requirements

- a tiered financial penalty structure.

Companies considering implementing EPA initiatives will have to operationalize information governance strategies which are fully in line with GDPR requirements. High-maturity business analytics organizations derive value by effectively embedding information governance policies, toolkits, and practices which align business needs to growth in analytics sophistication. There may be a need to develop regulatory frameworks which support the validation of EPA initiatives. We envisage that such frameworks could possibly persuade an enterprise to collaborate within a community of organizations that 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 healthcare industry where manufacturers of wearable technology devices have established interconnected open source platforms where information can be exchanged to ensure the reliability of the devices while also alleviating security and privacy concerns [Piwek et al., 2016]. Another example includes the Connected and Open Research Ethics (CORE) initiative which aims to bridge the gap between manufacturers, researchers using wearable technologies and ethics boards tasked with protecting the research participants (e.g. legal implications of processing personal data).

4.3.5   Quality Assurance

In highly regulated environments, organizations must equip themselves with the requisite tools and safeguards to ensure that their information is transparent and above all accurate. Consequently, business analytics competencies and data management tools have become strategic priorities in organizations. A data quality dimension is a set of data quality attributes that represent a single aspect of data quality [Wang and Strong, 1996]. According to Jugulum [2016] there are four-core data quality dimensions (see Table 4.2) which can be used to measure data quality levels and reliability. In a EPA context, these four-core dimensions become critically important because 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]. In order to advance the science of EPA, 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]. When implementing EPA initiatives, it is imperative for organizations to pair good data with appropriate analytical techniques. We recommend that for running high-quality personal data analytics should also strive for high quality data whereby "preparatory analytics and cross-examination of data will play a significant role" [Jugulum, 2016]. Additionally, as different forms of analytics exist, organizations must ascertain which align best with their business requirements.

Dimension	Definition
Completeness	The extent to which data are of sufficient breadth, depth, and scope for the task at hand
Conformity	The extent to which the data is following the set of standard definitions (e.g. data type, size and format).
Validity	Validity is defined as the extent to which data corresponds to reference tables, lists of values from golden sources documented in metadata, value ranges, etc
Accuracy	Accuracy is defined as a measure of whether the value of a given data element is correct and reflects the real world as viewed by a valid real-world source (e.g., SME, customer, hard-copy record, etc.).

Table 4.2 Four-Core Data Quality Dimensions [Jugulum, 2016]

Once again, lessons can be harnessed from the wearable technology industry where critics have questioned the quality of the individual data being generated. For example, there is considerable variation across wearable technology devices and sensors with regards to functions, data quality, and measurement approaches. According to Davenport and Lucker [2015], "the presence and size of a step taken are often a different construct from device to device. Sensors such as accelerometers are often developed by semiconductor and microelectromechanical systems firms, each of which may detect and measure something as simple as a step in a different fashion". To put it simply, if a user bought five different wearable tracking devices and compared various measurement dimensions, such as the number of steps taken, the number of hours slept or average heart rate, at the end of the day there would be considerable differences between them. Moreover, the manner with which these devices measure these dimensions would also vary. This leads to questions pertaining to what manufacturers do companies use for their EPA technologies and most importantly how do they ensure that all worker personal analytical data is successfully integrated. We envisage that the standards required to aggregate data across various monitoring devices could prove challenging. We would recommend for companies to partner with other organizations in order to collaborate on common data standards and issues pertaining to data integration.

We would also like to point out the significance of visualizing and interpreting EPA data. 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 more easily 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]. Ultimately, workers will benefit from having access to

sophisticated business tools within an enterprise setting enabling them to derive greater value from their personal data (e.g. improved decision making).

4.4   Summary

In this Chapter, we firstly introduced the concept of EPA, a term which we have coined to reflect a new business analytical phenomenon. Next, Table 4.1 presents a two-dimensional grid research framework which can be used to guide and bound future research in EPA. This framework comprises two distinct categories of EPA perspectives: stakeholders and concerns. In Chapter 5, we outline theoretical and practical implications, limitations and conclusions.

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Theoretical and Practical Perspectives, Limitations and Conclusion

While personal analytics scenarios have received attention in different research fields, this paper sought to gather the fragmented views pertaining to EPA and bring together researchers interested in the impact of this new phenomenon. Specifically, in an IS context, given that "ignoring individual IS within our discipline is an evolutionary oversight that may simply reflect our own assumptions that personal, individual IS are uninteresting: simple; or mostly recreational systems used after hours or outside of real organizational IS" [Baskerville et al., 2011]. Consequently, this monograph attempts to advance our understanding of the EPA concept. In this study, we have presented a 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. It provides a foundation for IS researchers to build upon, understanding other user cohorts in different work and personal situations. It also provides guidance to practitioners. Our hope is that the term "enterprise personal analytics" and our EPA theoretical framework and practical research visual mapping artefact are useful organizing concepts. In section 5.1, we discuss the theoretical implications of our research. To assist with future research, we have populated the two-dimensional grid with sample research questions which we argue merit further scrutiny in an EPA context. Next, in section 5.2, we delineate the practical implications of our research. To this end, we have also devised a visual mapping artefact which we have coined as the "EPA

metro map" which could be used by companies to plan and map their EPA digital transformation initiatives.

5.1   Theoretical Implications: Using the EPA Framework to Guide Future Research

Having examined the five core EPA concerns and the three perspectives (see Chapter 4), let's look back at the EPA digital transformation roadmap depicted in table 5.1. Our framework encourages a systematic focus and strives for a common understanding of the role of individual personal analytics within the enterprise. Only continued IS theoretical deliberations and rigorous evaluation and exploration of the perspectives and concerns identified within our framework will reveal whether EPA is here to stay or is just the latest in a series of technological trends or buzzwords. Consequently, this research represents one in an initial series of proposed studies through which we hope to advance the concept of EPA.

Table 5.1 EPA Two-Dimensional Grid Framework: (A) a multi-concern, single perspective study, (B) a single-concern, multi perspective study, (C) a single-concern, single perspective study

A novel feature of this "grid"-type roadmap pertains to the various permutations of research designs that can be operationalized. The first design is a multi-concern, single-perspective view denoted by the letter A. The second design is a single-concern, multi-perspective view denoted by the letter B. The final design represents a single-concern, single-perspective view denoted by the letter C. Given the rather infant status of the EPA phenomenon, we encourage future research to populate each of the cells within this grid framework. This will facilitate the

categorization of future research EPA studies within the IS discipline. To assist the process, we have devised sample high-level research questions that we believe merit further consideration (see table 5.2). We encourage future research to further break down these high-level research questions to investigate the EPA concept.

		Perspectives		
		Company	**Worker**	**Modality**
Concerns	**IIS Architecture**	What reference architectures are suitable for creating productive and interoperable IIS architectures for workers?	How can the company effectively develop a flexible IIS architecture that continuously facilitates worker learning and improvement?	How can IIS architectures contribute to the teams' and company's overall goals?
	Knowledge & IP	What data governance agreements can be put in place to handle scenarios in which workers request access to their EPA data when they leave the company?	How can workers create and analyze knowledge in a meaningful way?	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 by 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, behaviors, and performance?
	Information Governance	How can the company minimize 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 interteam data transfers?
	Quality Assurance	Who or what algorithms govern the analysis and presentation of personal analytics data?	What specific individual worker metrics can contribute to organizational KPIs in a meaningful way?	What digital tools can workers use to ensure the effective sourcing and subsequent analysis of their personal data?

Table 5.2 EPA research framework example questions [Clohessy and Acton, 2017]

Furthermore, there is a significant need for EPA business use cases and EPA adoption frameworks. In our analysis, extant research suggests [see Lansiti and Lakhani, 2017] that two dimensions impact how a disruptive technological trend and its business use case evolves. The first is complexity which is represented by the level of coordination required by all parties in an organizational ecosystem to produce value with the technology. The second dimension is novelty which describes the level of effort a user requires to understand the problems that the new technological trend can solve. The more novel a concept is, the greater the learning curve. We encourage companies to develop adoption frameworks which map possible EPA implementations against these two aforementioned dimensions which can vary from low to

high in terms of the stage of technology development. For instance, companies new to the EPA concept may want to introduce an EPA pilot programme which is low in novelty and low in complexity (e.g. use of wearable fitness trackers to reduce the organization's insurance scheme premiums).

5.2   Practical Implications

To advance the emergence of EPA business use cases we have also devised a visual mapping artefact (see figure 5.1) which we have coined the "EPA digital transformation metro map" which depicts possible routes which companies must navigate for the five concerns across the three perspectives raised in this article. We have provided the following colour codes for the individual routes for the five concerns: IIS architecture (pink), knowledge and IP (blue), quality insurance (yellow), information governance (red) and motivation and remuneration (green). For illustration purposes, we have only completed the journey for the *IIS architecture* concern (e.g. the pink route). This specific 'pink route' comprises possible 'route stops' which must be considered by organizations in terms of design (e.g. security, applications, and process architectures), reference architecture (e.g. business continuity management, analytics sources), initiatives (e.g. flexible architectures to ensure continuous learning), systems integration (e.g. legacy systems), investments (e.g. wearable technology vs desktop monitoring), change management (e.g. new employee onboarding), requirements (individual vs group) and IIS vision (e.g. alignment with main EPA strategy). We must stress that we have only used these specific route stops for illustration purposes and we encourage industrial organizations to carry out pilot EPA projects to identify specific 'route stops' which are the best fit for their organizations for all of the concerns outlined in this paper.
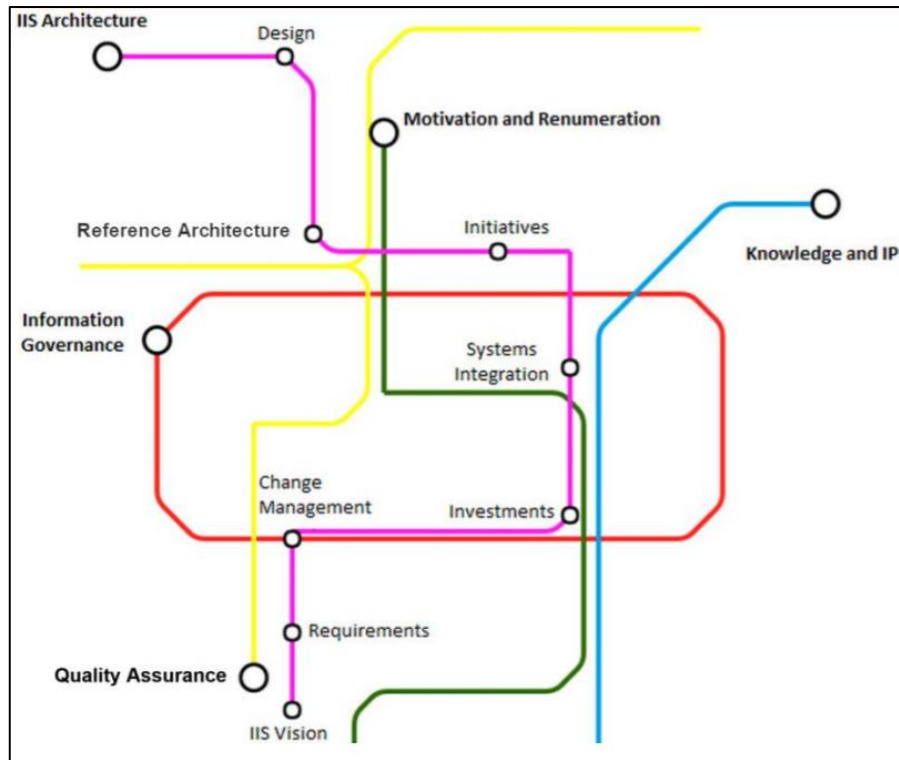
Figure 5.1 EPA Digital Transformation Metro Map

5.3 Limitations

The following limitations should be kept in mind when considering the findings of this paper. First, 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. Additionally, there are potentially research resources that investigate similar phenomena but discuss it with different terms, and thus, were difficult to find. We found throughout our survey of the literature that the only consistency pertaining to the concept of personal analytics is inconsistency. This fluid state of the personal analytics field in conjunction with the subjective nature of the literature review filtering process – necessary due to the inconsistent use of the term across disciplines/fields – limits this work. However, at the same time, it seems that increasing the focus would not change the general conclusions or provide additional insights. Further, our analysis, which is based on a holistic integration of ideas across various research strands provides a strong theoretical grounding from which IS researcher can operationalize future research studies in the area. Second, we would also like to acknowledge the potential for

researcher bias. From the initial study design, through to the development of the methodology and the reporting of the findings, the study made use of an audit trail and audit process [Schwandt, Lincoln and Guba, 2007]. This ensured that the study was underpinned by rigour, authenticity and neutrality. We have provided sufficient details on our methodology (see Chapter 2) so that IS researchers can either replicate our study or consider the extent to which our findings can be compared to or transferred in other contexts.

5.4   Conclusion

Global businesses are increasingly embracing the use of personal digital technology in the workplace. For instance, wearable technologies are providing capabilities that are completely new to mainstream business practices (e.g. Tobii's EyeX, SMI eye tracking glasses). While the mainstream application of EPA in an organizational setting remains relatively niche, we believe its impact will fundamentally change enterprises across all sectors. For instance, we envisage that industrial sector organizations will be at the forefront of the EPA drive with "the bulk of data from emanating sensors within an 'the industrial internet,' comprising a very large number of networked devices in plants, transportation networks, energy grids, and so forth" [Davenport. 2014]. In lieu of the current personal data polemics (e.g. high-profile instances of personal information data leaking), we believe that if organizations behave appropriately and build a culture of trust, companies, and workers (and customers) will become acclimatized to capturing and analyzing their personal data within an enterprise setting. Organizations need to proactively prepare themselves for this change as EPA is coming to a company near you soon!

In summary, this monograph 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 significant analytical developments which have shaped the emergence of the EPA concept, (2) it provides a holistic framework which aims at synthesising and advocating future research in the promising area of EPA, (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 EPA digital transformation initiatives.

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