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A cognitive analytics management framework for the transformation of electronic government services from users' perspective to create sustainable shared values

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ABSTRACT

Electronic government services (e-services) involve the delivery of information and services to stakeholders via the Internet, Internet of Things and other traditional modes. Despite their beneficial values, the overall level of usage (take-up) remains relatively low compared to traditional modes. They are also challenging to evaluate due to behavioral, economical, political, and technical aspects. The literature lacks a methodology framework to guide the government transformation application to improve both internal processes of e-services and institutional transformation to advance relationships with stakeholders. This paper proposes a cognitive analytics management (CAM) framework to implement such transformations. The ambition is to increase users' take-up rate and satisfaction, and create sustainable shared values through provision of improved e-services. The CAM framework uses cognition to understand and frame the transformation challenge into analytics terms. Analytics insights for improvements are generated using Data Envelopment Analysis (DEA). A classification and regression tree is then applied to DEA results to identify characteristics of satisfaction to advance relationships. The importance of senior management is highlighted for setting strategic goals and providing various executive supports. The CAM application for the transforming Turkish e-services is validated on a large sample data using online survey. The results are discussed; the outcomes and impacts are reported in terms of estimated savings of more than fifteen billion dollars over a ten-year period and increased usage of improved new e-services. We conclude with future research.

1. Introduction

The Internet has been having a transformational effect on our society, and governments worldwide have been undertaking various initiatives to improve the efficiency and effectiveness of internal operations, communications with citizens and transactions with organizations with the aim to encourage the adoption of electronic government (e-government) initiatives. E-government involves the delivery online of government information and services to various stakeholders using the Internet, Internet of Things, and traditional modes for cutting-cost ideas in government, Welsh (2014). Stakeholders include citizens; non-citizen and business users; government employees; information technology developers; government policy makers; public administrators and politicians; and organizations, Rowley (2011). E-government services (e-services) have been developed to achieve various environmental, financial, political and social beneficial goals, Chircu (2008). Despite such benefits, they have several challenges including governance; policy development; information management; technological change; societal trends; and human factors, Dawes (2009). E-services require high capital investments and have a limited take-up rate from users, Lee et al. (2008). The take-up rate

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is measured by the percentage of individuals aged between 16 and 74 who have used the internet for interacting with public authorities, (UN-Survey, 2012). It was reported that the expenditures on information and communication technology were 2.4% and 0.9% of the Gross Domestic Products of the 27 European Union states (EU27) and Turkey, whereas the take-up rates of e-services were 28% and 9% in EU27 and Turkey, respectively, EU-Archive (2010). The low usage limits the impact of e-government services, and more research needs to be done if governments are to successfully leverage e-government services and realize other benefits, (UN-Survey, 2012). In response, an EU i2010 initiative on inclusive government was launched to achieve a government goal "close the digital divide - no citizen to be left behind" through the provision of improved e-services. Given the low take-up rate in Turkey, the Turkish agency in charge of the provision of e-services, has similarly endorsed the EU i2010 inclusive initiative and participated in this research project as an industrial partner. It should be noted that the digital divides include access; affordability; age; education; bandwidth; content; gender; mobile coverage; internet speed; and useful usage among others, (UN-Survey 2012). It was envisaged that the inclusive government initiative can be achieved using *two ways of government transformation*, EU-Archive (2010): one transformation of internal processes to *improve e-services*; and another institutional transformation to *improve relationships* between governments and stakeholders for a creation of sustainable shared values. Shared values are often created using innovative ideas based on the interface of measurement and management to balance the various tradeoffs when making long and short terms transformative decisions, Osman and Anouze (2014a). Shared value is measured by the total sum of business value to shareholders and the other economic, environmental and social values to other stakeholders, Porter and Kramer (2011). Luna-Reyes and Gil-Garcia (2014) reported that there was little or no evidence of government transformation applications; and such applications may occur in the future. Therefore, our research goal is to propose a methodology framework to guide the government transformation application to improve e-services, and to improve the relationships between governments and its stakeholders, thus leading to an increase in the take-up rate of e-services and the creation of sustainable shared values to all stakeholders. The associated research questions include: (a) How can an e-service be improved? Can we the efficiency and effectiveness of an e-service be measured? (b) How can the relationship between government and citizens be improved? Can the characteristics of satisfaction of users be identified to increase the usage of e-services? (c) What are the estimated shared values to the stakeholders of e-services in Turkey? (d) What is the methodology framework to guide the government transformation application to achieve the various objectives?"

Reviews of the literature on addressing the *low take-up* challenge identified the followings. Millard (2008) called for improving the performance of e-services with a special focus on measuring the efficiency utilization of input resources and the effectiveness of generated outputs and impacts from users' perspective. Whereas, Lee et al. (2008) and Petter, DeLone, and McLean (2008) suggested to improve users' satisfaction with e-services to increase the take-up rate. While reviews on *methodologies* for evaluating e-services listed several challenging aspects including: *identification of measures on users' attitude and behavior* (knowledge of technology; personal traits and behavioral change during online interactions with e-services), Magoutas and Mentzas (2010); *implementation* of ICT processes (breaks of Internet connectivity and communication systems, internal disintegration and operability, electronic system's security, and service development), (Weerakkody, Irani, Lee, Osman, & Hindi, 2015; Yildiz, 2007); *inappropriate usage of methodologies to identify the*

best-practice benchmark (lack of tools for improving inefficient e-services), (Irani et al., 2012; Osman et al., 2014a); and *inability to analyze qualitative and quantitative data* on environmental, financial, political, and social dimensions, (Bertot, Jaeger, & Grimes, 2010; Chircu, 2008). Further reviews on *evaluation methodologies* can be found in Irani et al. (2012), Osman et al. (2014a), Weerakkody et al. (2015) and Petter et al. (2008). These reviews showed that the majority of methods builds conceptual frameworks or apply statistical and *descriptive analytics* using fragmented measures for different reasons and from mixed perspectives rather than using holistic measures to perform *prescriptive and predictive analytics*.

Although, the existing studies were useful in providing a good understanding of the complexity of evaluating e-services, and in identifying factors of satisfaction on users of e-services, they have a number of limitations, (Irani et al., 2012; Weerakkody et al., 2015). First, *subjective data* obtained from off-line distributed surveys may contain transformation errors and bias. Whereas, experiential data obtained immediately from online surveys after a completion of interactions with an e-service can be of better quality, and free from subjective bias and errors found in traditional offline surveys (Chen, 2010). Second, *statistical methods* are useful in establishing relationships among variables and capable of predicting trends, Petter et al. (2008). Third, they may consider the set of most efficient (and inefficient) e-services as *outliers* to drop from the statistical analysis for the sake of generating average trends, (Lee & Kim, 2014). Hence, they may not be the most appropriate methods for conducting benchmarking analysis to identify the set of efficient e-services (best practice benchmark) to suggest improvement targets for the set of inefficient e-services where *frontier analytics* are more appropriate for benchmarking the quality of e-services. Last, they have other limitations on multi-collinearity assumption, normality of data, large sample sizes, and internal validity of measures, Norris and Lloyd (2006).

Reviews of the literature on emerging *prescriptive* methodologies for evaluating the performance *efficiency* of operations showed that *Data Envelopment Analysis* (DEA) is one of the most popular methods with over 485,000 hits on Google. DEA was introduced by Charnes, Cooper, and Rhodes (1978) to evaluate the relative performance efficiency of operating units (often called Decision Making Units- DMUs). DEA aggregates multiple-input and multiple-output measures using data-driven *variable* weights to generate a relative efficiency score for each DMU. The efficiency score measures the quality of transformation of inputs into outputs. DEA can also identify the best-practice benchmark (or the set of efficient DMUs) to suggest improvement targets for the set of inefficient units. In the literature, there are a large number of relevant DEA applications. Cook and Zhu (2006) developed a DEA model for treating qualitative data with ordinal Likert Scale values. They showed that qualitative rank ordered data can be treated in a conventional DEA methodology. De Witte and Geys (2013) argued that the citizens' coproduction of public services require a careful measurement of productive efficiency. They presented a DEA application to measure the technical efficiency of citizens' co-production in the delivery of library services. Osman, Berbary, Sidani, Al-Ayoubi, and Emrouznejad (2011) used DEA to assess the performance efficiency of nurses at an intensive care unit using Likert scale values. An appraisal and performance evaluation system was developed for a better motivation of nurses. It corrected the evaluation bias which was found in a traditional approach based on fixed weights to combine measures. Esmaeili and Horri (2014) used a fuzzy DEA approach to evaluate the satisfaction of customers with online banking services using variables with qualitative values. For more details on the DEA theory and applications in the public and private domains; we refer to the handbook on strategic performance measurement

and management using DEA in Osman, Anouze and Emrouznejad (2014); and to the special issue on DEA in the public sector by Emrouznejad, Banker, Lopes, and de Almeida (2014).

Reviews of the literature on *predictive* methodologies for the prediction of satisfaction classes and characteristics of satisfied users showed that Classification and Regression Tree (CART) is one of the most popular methods, it received more than 291,000 hits on Google. CART was first developed by Breiman, Friedman, Olshen, and Stone (1984) to identify classes of common characteristics from the construction process of a tree of predictors. It has attracted a number of applications. Oña, Eboli, and Mazzulla (2014)) used CART to determine the most important variables which affect changes in the quality of transit services. However, *DEA and CART* methodologies are often combined in a *two-stage* approach, which has attracted more than 6070 hits on Google. Applications include the work of Emrouznejad and Anouze (2010). They used DEA in the first stage to generate relative efficiency scores for banks, whereas CART was used in the second stage to identify the characteristics of profitable customers in the banking sector. Chuang, Chang, and Lin (2011) used DEA to measure the operational-efficiency and cost-effectiveness of medical institutions while CART was used in the second stage to extract rules for a better resource allocation. De Nicola, Gito, and Mancuso (2012) applied a Bootstrapping approach to the DEA efficiency scores to increase the confidence in the quality of DEA results, before conducting CART analysis to determine the environmental variables which impact the performance of the Italian healthcare system. Biener, Eling, and Wirfs (2016) also used DEA and Bootstrapping models to evaluate the efficiency production of Swiss insurance companies. Li, Crook, and Andreeva (2014) used DEA to measure the technical and scale efficiencies of some Chinese companies. The two efficiency measures were introduced into a logistic regression model to predict the distress probability of a particular company. Horta and Camanho (2014) used DEA and CART models to characterize the competitive positing of Portuguese construction companies. They argued that the DEA–CART approach can bring new insights and identify classes of competitive companies. They generated DEA efficiency scores from financial data and identified by CART the non-financial characteristics of efficient companies.

The previous studies demonstrated the importance of the Operational Research/Management science (OR/MS) in providing the academic rigor in modeling and solving problems. However, Business Analytics (BA) is a growing faster and becoming more popular than OR/MS. Searching for BA on Google, it returned 7440,000 hits, compared to 2750,000 hits for OR and 11,500,000 hits for MS. BA presents a genuine challenge to the OR/MS community, Mortenson, Doherty, and Robinson (2015). Rayard, Fildes and Hu (2015) argued that if OR are to prosper; it must reflect more closely the needs of organizations and practitioners. Further, Vidgen, Shaw, and Grant (2017) highlighted that challenges of data and management are often marginalized and even ignored in the OR context, but they are essential for organizational managers who seek to become more data-driven creators of shared values.

The above review of the literature shows a lack of a methodology framework to guide the government transformation application to improve both the internal processes of e-services and the institutional transformation to advance relationships with stakeholders; to increase the usage of e-services for creating sustainable shared values to all stakeholders. The innovative methodology framework brings together the OR/MS academic rigor and the BA practical relevance in the context of electronic government. It consists of three interconnected closed-loop strategic processes. *First*, the *cognitive process* is to understand the evaluation (business) challenge and frame it into analytics terms. The framing process identifies the questions to answer, the goals

to achieve, and the data guideline and processing requirements to be understood by technical teams. For instance, it provides the necessary understanding of the human–machine interactions with e-services and the underlying factors that affect the satisfaction of users. It designs the data strategy; identifies the performance variables, data types, and collection sources; define data governance and ethics. It further builds the data model to align and map the identified variables to the defined organizational goals and objectives. *Second,* the *analytics process* employs the right mix of advanced modeling and solving methodologies to address the complex challenge in evaluating the performance of e-services. The analytics process combines both the Data Envelopment Analysis (DEA) and the classification and regression trees (CART) methodologies in a two-stage approach. In the first stage, DEA generates the input-efficiency and output-effective scores for each e-service, computes an individual satisfaction score for each user and identifies the set of efficient of e-services (the set of best-practice benchmark) to improve inefficient e-services. In the second stage, the individual DEA scores and the qualitative characteristics of users are analyzed using CART to predict the characteristics of satisfaction classes and prescribe corrective policy recommendations for managerial actions. Last the *management process* defines the engagement and coordination among senior managers, providers and research team during the execution of the analytics project. The senior management further sets the strategic goals and objectives to be achieved. Senior managers have an important role in fueling the organization digital culture for the assurance of a successful implementation of the government transformation application. Those seniors have to be convinced before they can support any digital technology innovation to address challenges. Therefore, the management process is needed to provide the closed-loop linkage between the cognitive and analytics processes.

In summary, the main contribution of the paper is to propose a cognitive analytics management (CAM) methodology framework to guide the transformation of Turkish e-services to achieve the Turkish Government goal in implementing its digital inclusive initiative to close the digital divide through improved performance e-services, increased satisfaction of users, and creation of sustainable shared values to all stakeholders. To the best of our knowledge, the CAM framework is the first OR/MS contribution to the modeling of human–machine online interactions in the electronic government domain. It builds on the academic OR modeling rigor and practical BA relevance to advance electronic government research. The specific research objectives include: (i) introducing a cognitive process to understand and frame the human–machine interactions with an e-service in analytics terms; (ii) introducing analytics models and solving processes to evaluate the efficiency of an e-service and measure the satisfaction of users during their online human–machine interactions, hence providing a new research avenue to understand the human–machine online interactions in the electronic government context; (iii) using the DEA methodology to develop performance indices for the input-efficiency and output-effectiveness of e-services, and to measure satisfaction of users with e-services; (iv) proposing a tool to identify the set of efficient e-services (best-practice benchmark) to guide the improvement process of the inefficient e-services; determine the variables and associated target improvement levels with reference to the best-practice benchmark; (v) identifying characteristics of the different satisfaction classes of users using CART to develop social inclusion policies for managerial actions.

The remaining part of the paper is organized as follows. Section 2 presents a literature review on the existing methodologies for the evaluation of e-services. Section 3 introduces each process of the proposed CAM framework. Section 4 presents and discusses our experience and results. The final section concludes

with managerial implications, practical impacts, and limitations for further research directions.

2. Review of evaluation studies on e-government services

Many of the models and frameworks for the evaluation of e-services are adapted from the e-commerce literature; they investigate users' attitudes and satisfaction with e-government services. Appendix 1 presents taxonomy of developed methodologies to evaluate e-services with special focus on the measured objectives, evaluation methodologies, analytical models and associated variables. The following observations can be made. The various methodologies developed over time have one of the following objectives to evaluate: (a) *system success*, (b) service *quality*, (c) government *value*, and (d) users' *satisfaction index. First,* the e-service success model was built on the well-known information system success model introduced by DeLone and McLean's (1992). It consists of six measurement factors: system quality; information quality; service quality; system use; user satisfaction and net benefits. *Second,* the e-service quality model was built on the SERVQUAL model introduced by Parasuraman, Zeithaml, and Berry (1998). It consists of five factors: tangibles; reliability; responsiveness; assurance and empathy. *Third,* the e-service value model (VM) was introduced by Harvard University to assess the value and usage of e-government websites and e-government projects, Mechling (2002). The VM model is conceptual and based on five-value factors: direct-user value; social/public value; government-financial value; government operational/foundational value and strategic/political value. In the value category, a commissioned-evaluation study for the Australian government was presented by Alston (2003). The study provided estimated measures on e-government costs and benefits to both users and government agencies. The estimated measures were midpoint values of the financial benefits and costs over a period of 5 years. The estimates were solicited from e-government agencies. The estimated results provided useful information, but given the difficulty of getting those estimates, it was advised to interpret them with caution. *Fourth,* the cost-benefit and risk-opportunity analysis (COBRA) model was developed to measure the satisfaction values of users with e-services based on 8 factors, Osman et al. (2014a). *Last,* other satisfaction models were adopted from traditional customer satisfaction indices in different countries to identify key drivers of satisfaction with products and services, (Kim, Im, & Park, 2005). They were extended to evaluate satisfaction with e-services using surveys. The importance of using surveys to measure satisfaction of citizens was discussed in Van Ryzin and Immerwahr (2007). Further, Grigoroudis, Litos, Moustakis, Politis, and Tsironis (2008) used surveys data and multi-criteria regression models to assess users' perceived web quality and to measure users' satisfaction with the service provisions by three major cellular phone companies in Greece. More details on other satisfaction methodologies in the electronic government research can be found in Irani et al. (2012).

Finally, there is a lot of literature on evaluating e-government services from providers' perspective. For instance, Chircu (2008) reviewed the electronic government research published in the period 2001–2007; and found that most of the research contributions on e-services were focused on US (45%), UK (11%), Singapore (7%) and (37%) for the rest of the world. The evaluated objectives were measured in percentages of coverage in the published papers: 63% addressed *financial objectives* to achieve reduction in cost, time and labor savings for maintaining the current service levels, and avoiding cost-increase for the provision of better service levels; 65% focused on *social objectives* to provide effective e-service deliveries, information dissemination, sustainable shared value creation and better resource allocation; and finally 44% discussed *political* objectives to enable democracy, transparency, accountability, social jus-

tice and liberty. As a result, a conceptual framework was proposed using the identified financial, social and political dimensions from multiple stakeholders' perspective without any quantitative validation and analysis, Chircu (2008). Recently, a systematic review on electronic government research was conducted by Weerakkody et al. (2015). The overall derived view indicated that although a large number of papers discussing issues related to costs, opportunities, benefits and risks, the treatment of these issues tended to be *superficial*. They reported a lack of empirical studies to validate the relationships of the performance measures to various e-government systems and government transformation goals. Such analysis would help in the pre-adoption of digital government transformation and implementation by senior management.

Reviewing non-statistical studies for the assessment of customer satisfaction in other non-government domains shows the followings. *First*, k-means algorithm was used by Afolabi and Adegoke (2014) to identify the factors that contribute to customer satisfaction. It requires researchers to pre-specify the number of clusters (k) which is very difficult to estimate in reality. Another drawback of k-means, it does not record the quality of generated clusters for benchmarking analysis. *Second,* a multi-objective genetic algorithm (GA) was implemented by Liébana-Cabanillas, Nogueras, Herrera, and Guillén (2013) to predict the levels of trust among e-banking users using socio-demographic, economic, financial and behavioral variables. It was found that GA requires a long running time to find optimal solutions, converges to a limited region on the Pareto efficient frontier; and might ignore interesting solutions. An advanced technique based on Artificial Neural Network (ANN) was used by Shen and Li (2014) to evaluate the service quality of public transport. It was found that the ANN technique lacks interpretability at the level of individual predictors and is difficult to construct the network layers, and associated learning and momentum measures. *Finally*, a DEA model based on the SERVQUAL five dimensions using nominal and ordinal data was useful for conducting a benchmarking analysis to improve the quality of services by Lee and Kim (2014).

In summary, the above brief review highlights the existence of fragmented measures with a lack of unified methodologies for evaluating both satisfaction and efficiency of e-services from users' perspective. This lack requires conducting more research using experiential real-time data with a proper validation of measures; developing a comprehensive analytical model which can integrate various fragmented measures into a holistic framework to evaluate simultaneously both satisfaction of users as well as efficiency and effectiveness of e-services to identify managerial actions for improvement. Users of e-services unlike customers cannot switch to different government providers; if not satisfied, they can only opt not to re-use an e-service and stick to traditional modes. Therefore, this paper follows a bottom-up (user-centric) approach to determine satisfaction measures from real-time experience of users while interacting online with e-services. The identified measures can then be validated and analyzed using the proposed CAM framework to meet the desired goal of Turksat. A bottom-up or user-centric approach was followed due to the following reasons. It was reported that the usage rate was limited and had not kept up with the fast growing availability of e-services, (UN-survey, 2012). The percentage availability of basic e-government services has grown up by 91% compared to only 39% for the percentage usage of e-government services in the EU27 between 2005 and 2010. Therefore, users must be placed at the center of development and delivery of e-services; identifying the factors, that affects users' motivations, attitudes, needs, and *satisfactions* underlying intentions to use e-government services, would have a decisive influence on large adoption and use of e-services, Verdegm and Verleye (2009). A number of recent studies stressed the importance of studying the factors that influence citizens' behavioral intention to

adopt and use of e-government services. Citizens' *attitude* toward using e-government services was found to be the most significant determinant factors among other socio-technology, political and cultural factors by Al-Hujran, Al-Debei, Chatield, and Migdadi (2015). The significance of modeling the behavior of citizens to influence the adoption of e-government services was stressed in Rana, Dwivedi, Lat, Williams, and Clement (2017). They found that the attitude has a direct effect on adoption of e-services and it is influenced by the effort expectancy of user, the performance of e-services and the social influence. Similarly, the advantage of assessing e-services from users' perspective through measuring the users' satisfaction to increase e-participation was stressed by Kipens and Askounis (2016). For comprehensive reviews of literature on e-services' measures and relationships between satisfaction, impact, cost-benefit and risk-opportunity, and the adoption and intention to use of e-services by individuals and organizations, we refer to Osman et al. (2014a), Weerakkody et al. (2015) and Petter et al. (2008).

3. The cognitive analytics management methodlogies

The cognitive analytics management is a mission-driven (or goal-driven) approach for the transformation of organizations, people and systems to generate insights and create shared values. It generates data-driven insights to make informed decision, and suggests policy innovations for managing performance and transformation of e-services to achieve desired goals. It expands and integrate emerging scientific fields including: *Social cognitive* theory, Bandura (1986); *Analytics,* (Robinson, Levis, & Bennett, 2014); *Business analytics* (Pape, 2016); *Big data* (Structured, unstructured, and semi-structured data), Gupta, Kumar, Baabdullah, and Al-Khowaiter (2018); *Cognitive analytics,* Donaki (2014); and *Cognitive computing* (human–machine interaction, machine-machine interaction), Gupta et al. (2018). We shall present a brief discussion to provide the necessary support and background for the development of CAM framework and associated methodologies.

The *Social Cognitive Theory* (SCT) has not been fully used to examine the individual's behavior for adopting e-services despite being considered as one of the important theories in human behavior, Bandura (1986). Some of the SCT constructs such as anxiety, attitude, self-efficacy, social influence, outcome expectancy, and their links to behavioral intention toward using technology have been investigated in a number of studies on e-government adoption studies, Rana and Dwivedi (2015). Further, the *Cognitive Mapping Theory* (CMT) was used to better understand the decision-making interactions that took place across the management and implementation of e-government projects, Sharif, Irani, and Weerakkoddy (2010). CMT seeks to graphically represent the state of variables (organizational complexity, governance, methodological constraints, practitioner concerns, financial concerns, and fear of failure) within an e-government project by links with fuzzy weights to signify causes and effects relationships. The authors concluded that understanding of the broader social, political, user satisfaction and stakeholder contexts are imperative for effective decision making and e-government implementations; organizations must also define who is responsible for e-government projects, and senior management must engage with e-government investment decision processes to improve decision making. Robinson et al. (2014) of the OR/MS community defined *Analytics* as "analytics facilitates the realization of business objectives through *reporting of data* to analyze trends, creating *predictive* models for forecasting and *optimizing* business processes for enhanced performance". This definition stresses modeling and processing to conduct descriptive, predictive and prescriptive analytics. Big data analytics describe software tools to handle big-data attributes which are characterized by the 4-V data-models: *Volume,*
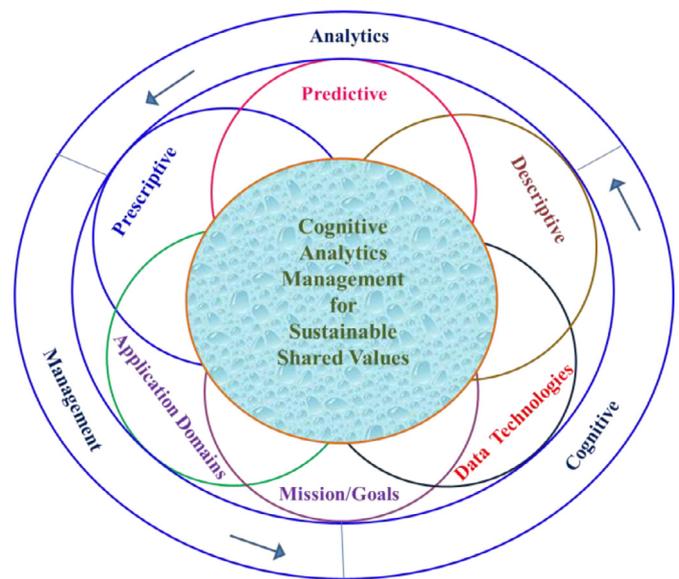

Fig. 1. The cognitive analytics management framework: processes and concepts.

Velocity, Variety and Value. Donaki (2014) of Deloitte consulting defined "*Cognitive Analytics*" as a new emerging term to describe *how organizations apply* analytics to make smart decisions; the new term attracts more than 63,900 hits on google, it is defined as a "field of analytics that tries to mimic the human brain in drawing inferences from existing data and patterns, it draws conclusions based on existing knowledge bases and then inserts this back into the knowledge base for future inferences – a self-learning feedback loop". Whereas the *Cognitive computing* term attracts more than 481,000 hits on google, it is defined as the *simulation of human thought processes* in a computerized model, (TechTarget, 2017). It involves *self-learning systems* that use data mining, pattern recognition and natural language processing to mimic the way the human brain works. Davenport (2006) stressed the need for organizations to compete on analytics. An analytics initiative requires the followings to assure success: an *enterprise-wide system* to ensure an easy access to critical data; a *widespread use* of a set of modeling and optimization tools beyond basic statistics for a comprehensive understanding of customers; and an *advocate team* of senior analytics leaders who have passion for analytics. Those analytics leaders set the right goals, objectives and analytics culture. They also provide support to acquire the right analytics tools, hire the right analytics talent and act on the data-driven insights and recommendations. Pape (2016) reported that the extract-transform-load process of cleansing data items from legacy systems and external sources to transfer them into an analytics system typically accounts for more than 50 per cent of the time and cost of any analytics project.

Given the above brief discussion on fragmented but useful approaches for the success of organizations in public and private sectors, we aim to propose our Cognitive Analytics Management framework to bring together three fragmented cognitive, analytics and management concepts into a unifying methodology framework to guide the implementation of digital transformation to address an organization's challenges. It brings together the best of all worlds in academic rigor and practical relevance with a special focus on the beginning and ending processes. Fig. 1 illustrates the interconnection and integration of the three CAM processes. The implementation of CAM starts with the cognition process to understand a challenge and frames it into analytics terms by building data models, identifying variables and relationships to align with the desired goals/objectives which are set in coordination with senior management. A data and governance strategy must be
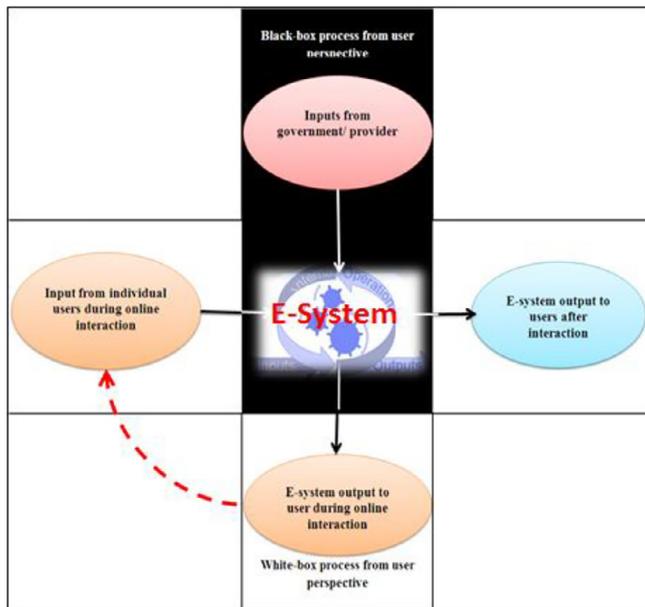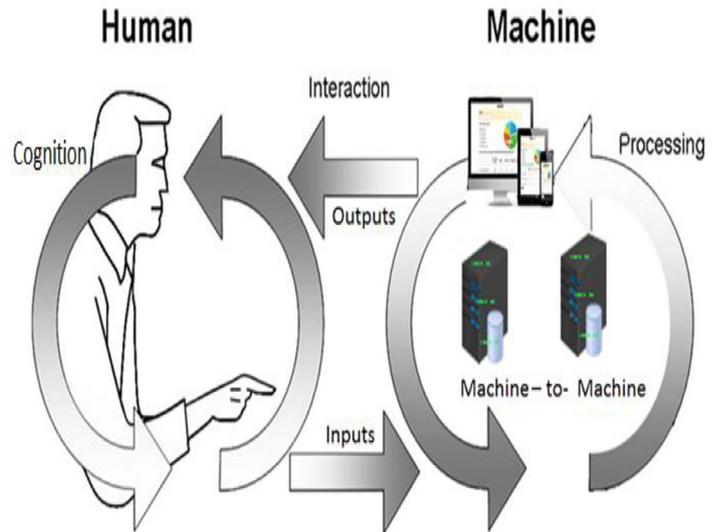
Fig. 2. A pictorial representation of the human–machine online interactions.

formulated for getting clean data using appropriate research processes, protection, and technology enablers in compliance with the General Data Protection Regulation (GDPR) guideline, Tikkinen-Piri, Anna Rohunen, and Markkula (2018). The cognition process typically accounts for more than 50 per cent of the time and cost of any analytics project, Pape (2016). The analytics process identifies the most appropriate analytics models and solving methodologies for addressing the identified challenge, and achieving the desired objectives; it also validates the results and communicates the analytics insights to senior management. Finally, the management process is the most difficult one. It is necessary for the assurance of successful implementation based on the derived managerial insights; it involves communications of results to other stakeholders to influence transformational actions. It requires crafting a message to stakeholders and fueling suggestions on this process. More discussions on each process are presented in the below sub-sections, whereas supporting details on CAM applications and creation of sustainable shared values can be found in Osman and Anouze (2014b).

3.1. The cognitive process for understanding and framing the evaluation challenge

The cognitive process is designed to understand the human–machine online interaction and to frame it into analytics terms. It analyzes previous findings to find out what has happened to determine the data management and compliance of research processes required to deliver quality data for processing at the analytics process. To be more specific, it is to understand the factors affecting performance and satisfaction of human; determine appropriate data models and metrics; validate relationships and alignment to the desired goals; and propose information technology processes to collect, store, retrieve and prepare data for analysis.

Fig. 2 provides an illustration of the human–machine online interactions with an e-service for a better understanding of the evaluation challenge. It is inspired by the social cognitive theory, Bandura (1986); and the cognitive computing systems, (TechTarget, 2017). It aims to understand the challenge in human–machine online interactions, Hollan, Hutchins, and Kirsh (2000). In cognitive systems, the psychological and physiological behaviors of a hu-

man during online interactions with a machine are captured using digital sensors/cameras to estimate human-intent to guide the movement of robotics, Kulic and Croft (2007). However, in our e-government online interactions instead of using sensors/cameras, *online surveys* are used to capture real-time behavior, attitude, intention and reaction, and economic values of users immediately after completing online sessions with an e-service. Fig. 2 illustrates the human–machine interaction with an e-service. The left part of the figure and the right part of the figure show the internal process (black-box for analytics engine) and the external process via a user interface (white box: computer/ mobile screen) while interacting with an e-government system The user interactions are then translated into a series of internal/external processes involving human–machine (external), machine-to-machine (internal) and machine-to-human (external) instructions to complete an e-service request. The final interaction delivers outputs on screen or on other external delivery modes such traditional mails, emails, mobile messages, etc. For more discussions on the human–man interaction cycles for the creation of shared values, refer to Osman and Anouze (2014c).

To evaluate the human–machine online interactions, a careful design is required for the identification of metrics to capture both human and machine characteristics. Critical reviews for the identification of the most critical factors and variables affecting users' satisfaction were published in Irani et al. (2012) and Weerakkody et al. (2015). The reviews led to the development of COBRA model for satisfaction, which consisted of a set of satisfaction metrics. This set contains 49 SMART (Specific, Measurable, Achievable, Relevant, Timely) metrics, which were statistically validated in Osman et al. (2014a). Table 1 provides a list of questions for each of 49 COBRA metrics divided into four COBRA factors and 8 sub-factors: Cost, (tangible, tC; and intangible, iC); Benefit (tangible, tB; and intangible, iB); Risk, (personal, pR; and financial, fR); Opportunity (service, sO; and technology, tO). The SMART metrics were derived using serval focus-group meetings conducted in UK, Turkey, Lebanon and Qatar involving users, professionals, academics and government experts to include new practical and relevant metrics not available in the literature. It turned out that COBRA model was the quantitative equivalent to the SWOT qualitative strategic model, (Jackson, Joshi, & Erhardt, 2003). SWOT evaluates company, service and product by generating improvement initiatives with references to internal processes and external competitors without

Table 1
COBRA validated measurable variables and associated labels (online survey questions).

No	Item/question	Label
1	The e-service is easy to find	tB
2	The e-service is easy to navigate	tB
3	The description of each link is provided	tB
4	The e-service information is easy to read (font size, color)	tB
5	The e-service is accomplished quickly	tB
6	The e-service requires no technical knowledge	tB
7	The instructions are easy to understand	tB
8	The e-service information is well organized	iB
9	The drop-down menu facilitates completion of the e-service	iB
10	New updates on the e-service are highlighted	iB
11	The requested information is uploaded quickly	iB
12	The information is relevant to my service	iB
13	The e-service information covers a wide range of topics	iB
14	The e-service information is accurate	iB
15	The e-service operations are well integrated	iB
16	The e-service information is up-to-date	iB
17	The instructions on performing e-service are helpful	iB
18	The referral links provided are useful	iB
19	The Frequently Asked Questions are relevant	sO
20	Using the e-service saved me time	tC
21	Using the e-service saved me money	tC
22	The provided multimedia services (SMS, email) facilitate contact with e-service staff	sO
23	I can share my experiences with other e-service users	sO
24	The e-service can be accessed anytime	sO
25	The e-service can be reached from anywhere	sO
26	The information needed for using the e-service is accessible	sO
27	The e-service points me to the place of filled errors, if any, during a transaction	tO
28	The e-service allows me to update my records online	tO
29	The e-service can be completed incrementally (at different times)	tO
30	The e-service removes any potential under table cost to get the service from E-government agency (tips)	tC
31	The e-service reduces the bureaucratic process	tC
32	The e-service offers tools for users with special needs (touch screen, Dictaphone)	tO
33	The information are provided in different languages (Arabic, English, Turkish)	tO
34	The e-service provides a summary report on completion with date, time, checkup list	tO
35	There is a strong incentive for using e-service (such as paperless, extended deadline, less cost)	tO
36	I am afraid my personal data may be used for other purposes	pR
37	The e-service obliges me to keep record of documents in case of future audit	fR
38	The e-service may lead to a wrong payment that needs further correction	fR
39	I worry about conducting transactions online requiring personal financial information such visa, account number	fR
40	Using e-service leads to fewer interactions with people	pR
41	The password and renewal costs of e-service are reasonable	tC
42	The Internet subscription costs is reasonable	tC
43	The e-service reduces my travel cost to get the service from E-government agency	tC
44	It takes a long-time to arrange an access to the e-service (the time includes: arrange for password; renew password; and Internet subscription)	iC
45	It takes a long-time to upload of e-service homepage	iC
46	It takes a long-time to find my needed information on the e-service homepage.	iC
47	It takes a long-time to download/ fill the e-service application	iC
48	It takes several attempts to complete the e-service due to system break-downs	iC
49	It takes a long-time to acknowledge the completion of e-service.	iC

*COBRA***:** intangible and tangible Benefit (iB and tB); intangible and tangible Cost (iC and tC); service and technology Opportunity (sO and tO); financial and personal Risk (fR and pR) Analysis.

prioritization. In the SWOT-COBRA analogy, the Cost, Opportunity, Benefit and Risk factors are equivalent to Weakness, Opportunity, Strength and Threat, respectively**.** With the appropriate use of analytics model to balance the tradeoffs between the various COBRA measures, satisfaction and prioritization insights with recommendations for improvement and resource allocations can be generated as discussed later.

Further the theoretical support to the CORBA selection of metrics for measuring satisfaction and performance values are provided below. *First*, the social exchange theory for interaction indicates that people invest in social exchange interaction if and only if the *cost and risk* inputs they put in the interaction are less than the *benefit and opportunity* outputs they get, (Blau, 1964). The e-service values to users have been largely ignored in empirical research; they play an important role in determining patterns of development, adoption, use and outcomes, Leinder and Kayworth (2006). *Second,* the expectation confirmation theory for satisfaction indicates that consumers are satisfied if the actual experience matches prior expectation, (Oliver, 1980). If users are satisfied with the e-services' website and application design, they are likely to share information about their successful experience through the use of social media networks, UN-Survey (2012). Such satisfaction would further encourage the citizen usage of e-services, Zheng and Schacter (2017). According to the equity theory for predicting individual's motivation and satisfaction behaviors, equity is measured by comparing the ratio of rewards (outputs) to efforts (inputs). Pritchard (1969) suggested that employees try to maintain a balance between what efforts they give to an organization (input efforts) against what they receive (output rewards) to base their satisfaction. As a consequence, individuals seek to maximize their net outcomes (rewards minus costs) or at least maintain equity between them. When individuals find themselves participating in inequitable relationships, they become distressed and dissatisfied. Using rational thinking, it is believed that when the benefits and opportunities (used as outputs) are greater than the costs and risks (used as inputs), the users will be more satisfied.

Table 2
DEA output-oriented and input-oriented constant return to scale (primal) models.

DEA-CRS-O: output-oriented primal model	DEA-CRS-I: input-oriented primal model
Maximize $\theta_p = \sum_{k=1}^{s} v_k y_{kp}$	Minimize $\varphi_p = \sum_{j=1}^{m} u_j x_{jp}$
Subject to:	Subject to:
$\sum_{j=1}^{m} u_j x_{jp} = 1$	$\sum_{k=1}^{s} v_k y_{kp} = 1$
$\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0; \; i = 1, \ldots, n$	$\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0; \; i = 1, \ldots, n$
$v_k, \; u_j \geq 0 \; \forall \, k, \; j$	$v_k, \; u_j \geq 0 \; \forall \, k, \; j$

3.2. The analytics process for evaluation

The analytics process to analyze the online experiential data is based on prescriptive analytics using Data Envelopment Analysis and prediction analytics based on a classification and regression tree (CART). Data Envelopment Analysis (DEA) models the human–machine interactions to find out what to do. DEA generates analytics results on the performance of e-services and the satisfaction of users. It establishes the best-practice internal benchmark to set target for improving inefficient e-services with reference to the established benchmark. A classification and regression trees (CART) model is used to analyze both DEA satisfaction score of each individual with associate characteristics to identify satisfied/dissatisfied classes for recommending social inclusion policies and prioritizing managerial actions to increase take up. The two analytics models are described next.

3.2.1. Data Envelopment Analysis (DEA) for satisfaction and performance evaluation

DEA is a nonparametric linear programming approach. It is proposed to evaluate the relative performance efficiencies of a set of e-services. These e-services are called decision-making units, (DMUs) in DEA terminology. Each DMU utilizes multiple-input resources (costs, risks) to transform them into multiple-output returns (benefits, opportunities) to measure satisfaction and performance. DEA generates a relative score for each DMU indicating the quality of transformation by comparing the DMU to its peers. The DEA score is an aggregated value, which is defined as the ratio of the total sum of weighted outputs over the total sum of the weighted inputs. The weights for the inputs and outputs are not fixed values, like in statistics, but they take variable values. These variable weights are optimized in the best interest of the DMU being evaluated subject to relativity performance constraints indicating that the performance of each DMU should not exceed 1. A DMU with a DEA score of 1 is called efficient, whereas a DMU with a score less than 1 is called inefficient.

In the literature, there are two basic DEA models. *First*, a DEA model assumes that all DMUs are operating under the *homogeneity* assumption of *Constant Return to Scale* (DEA-CRS), Charnes et al. (1978). Further the DEA-CRS model can be sub-divided into *input-oriented* and *output-oriented* DEA models. The output-oriented model maximizes the total sum of weighted outputs to generate an *output-effectiveness* performance value for each DMU and suggests recommendations for increasing outputs at a fixed level of the multiple inputs. The *input-orientation* model minimizes the total sum of weighted inputs to generate an *input-efficiency* performance value and suggests recommendations for reducing the utilization of inputs at a fixed level of the multiple outputs.

Table 2 provides linear programing formulations for the input-oriented (DEA-CRS-I) model and the output oriented (DEA-CRS-O) model under constant return to scale assumptions. For each DMU ($p = 1, \ldots, n$) in a set of homogenous DMUs for evaluation, (m) represents the number of input variables and (s) represents the num-

Table 3
DEA input-oriented and output variable return to scale envelopment (dual) models).

DEA-VRS-I: DEA input-oriented dual	DEA-VRS-O: output oriented dual
Minmize θ_p	Maximize φ_p
Subject to:	Subject to:
$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_p x_{ip}; \forall i$	$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ip}; \forall i$
$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rp}; \forall r$	$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \varphi_p y_{rp}; \forall r$
$\sum_{j=1}^{n} \lambda_j = 1$	$\sum_{j=1}^{n} \lambda_j = 1$
$\lambda_j \geq 0; \; \forall j = 1, \ldots, n; \; \theta_p$ free	$\lambda_j \geq 0 \; \forall j = 1, \ldots, n; \; \varphi_p$ free

ber of output variables; x_{jp} is the utilized amount of input j, y_{kp} is the generated amount of output k; and v_k, u_j are the weights assigned to output k and input j, respectively. The optimized weights can be seen as the optimal values for the returns and the costs of the resources that would make the associated DMU as efficient as possible in the relative evaluation process. The quality value of the transformation for a DMU (p) is obtained by maximizing a non-linear objective performance function. It is expressed by the ratio ($\sum_{j=1}^{s} v_k y_{kp} / \sum_{i=1}^{m} u_j x_{jp}$) subject to no performance ratios exceed one. This objective ratio is linearized in two different ways to generate the input and output oriented linear models as follows. The DEA-CRS output-oriented linear model is generated by setting the denominator of the non-linear objective to 1, whereas the DEA-CRS input-oriented linear model is obtained by setting the numerator to one. Table 3 provides the two formulation models in columns one and two, respectively. The set of n constraints in both models imposes the relativity concept that no ratio should exceed one.

Further, since one of the objectives of the DEA evaluation is to identify the set of efficient DMUs to establish a benchmark and to set targets for improving the inefficient units; each of the DEA-CRS models needs to be executed as many times as the number of available DMUs to derive the DEA efficiency scores for the DMUs. The DEA-CRS models assume *homogeneity* of DMUs. According to Dyson, Allen, Camanho, Podinovski, Sarrico, and Shale (2001), the source of non-homogeneity (heterogeneity) of DMUs comes from different environments or economies of scale. In the context of e-government services, the human–man interactions with an e-service (DMUs) are heterogeneous due to the existence of interactions from locations with more or less attractive internet speeds (environment) or involving people having different knowledge and technical skills; they are all interacting with an e-service using different input resources to receive the same output level or interacting with different e-service types (informational, transactional, and interactional) using the same input level to receive different output levels. Such differences lead to heterogeneous human—machine interactions operating under variable increasing or decreasing variable return to scales. To address, the non-homogeneity (heterogeneity) issue, a variable returns to scale (DEA-VRS) model has been developed specifically to accommodate scale effects in analysis, Banker, Charnes, and

Cooper (1984). They are based on the duality theory of linear programing, in which the DEA-CRS primal model is augmented by adding a new constraint ($\sum_{j=1}^{n} \lambda_i = 1$) to allow for variable returns to scale in the envelopment dual models; where the set of (λ_i)s represents the dual variables of the constraints in the linear programing primal model associated with DMU (i). Table 3 provides linear programming formulations for the input-oriented (DEA-VRS-I) and the output oriented (DEA-VRS-O) envelopment dual models under variable return to scales.

It is known that one of the most important steps in the DEA analytics modeling process is the *definition* of DMUs and the *identification* of associated multiple-input and multiple-output variables to achieve the organizational desired goal. The set of human–man online interactions will be used to define the set of decision-making units (DMUs). The COBRA metrics would then be used to define the set of multiple-input and multiple-output variables, respectively. The set of online interactions (DMUs) would then be evaluated using the DEA models to determine a relative satisfaction of each user based on the individual experiential interactions with a particular e-service. The DEA scores derived for all users from the DEA-VRS input-oriented model would be averaged to provide an input-efficiency score on the performance of a particular e-service. Similarly, the derived DEA scores from the DEA-VRS output-oriented model would provide an output-effectiveness score on the performance of an e-service.

The major advantage of DEA Model lies in the simplicity of solving after careful modeling of the underlying problem. It does not require an objective function to express the transformation of inputs into outputs. But it does require the total number of DMUs over the total sum of inputs and outputs to be sufficiently large for a proper discrimination among DEA units, Osman et al. (2011). The major DEA disadvantage, it does not provide a statistical inference on the derived DEA scores due to random errors in data inputs or data correlations between metrics and users' trait. As a result, a potential efficiency bias in the DEA scores may happen. To address this disadvantage, Simar and Wilson (2007) suggested implementing DEA models with a *bootstrapping* technique to produce estimate values for the lower and upper confidence bounds for the averages and medians of the original DEA scores. They suggested using a simple sampling procedure to draw with random replacement from the same sample of DEA scores, thus mimicking the underlying original data generation process.

3.2.2. Classification and regression trees (CART) for classification

Classification and regression trees (CART) model – is a non-parametric methodology. It is proposed to construct a tree structure to identify classes of users based on their DEA satisfaction scores (dependent) and characteristics as (independent) predictors. CART model recursively partitions the dataset of users (population) into smaller meaningful subclasses to improve the fit within each subclass as much as possible. The partitioning process uses a simple decision tree structure to visualize the identified classes. The major components of CART model are the *partition and stopping* rules. The partition rule determines which node (among predictor variables) to select for splitting the population at each stratification stage. The stopping rule determines the final constructed strata (branches of tree with different characteristics). Once the strata have been created, the *node impurity* of each stratum is assessed based on heterogeneity measures. There are three heterogeneity criteria to assess a node impurity: Misclassification error, Gini index, and Cross entropy. The Gini index of node impurity is the most commonly used measure for classification. The impurity measure reaches a minimum value of zero when all observations included in a node belong to the same purity class, and a maximum value when the different classes at node are equal sizes. However in regression trees, the measure of impurity is based on

the least squared differences between the observed and predicted values.

CART models are not as much popular as traditional statistical methods due to the short span of existence. However, they have several implementation advantages: (i) the analytical results are easy to explain, and interpret; the segmentation of population into meaningful classes is often obtained from the visualization of the constructed tree structure; (ii) CART models are non-parametric and non-linear in nature. They do not make any statistical assumptions on normality, non-collinearity, and other requirements of conventional methods (like discriminant analysis and ordinary least square methods) (iii) CART model can handle all data types whether numerical or categorical. As a result, they become one of the most powerful visualization analytics tool, Hastie, Tibshirani, and Friedman (2009). However, they are not without disadvantages. A researcher cannot force a particular predictor variable into CART model. It might be omitted from the list of predictors in the final tree if such predictor was found not necessarily significant. In such case, traditional regression models might be more appropriate, Gordon (2013). Finally, for more details, we refer to the good book on statistical learning by Hastie et al. (2009), and the review on CART development and applications by Loh (2014).

3.3. The management process for setting goals and managerial actions

The management process is an essential component of CAM framework for the initiation and successful completion of any analytics project. Senior management sets initially the strategic goals and objectives such as closing the digital divide through enhancing users' satisfaction and providing more improved e-services. They approve access to systems, and enforce adherence to data governance policies. Senior management also synchronizes and coordinates the interactions among stakeholders (policy makers, internal technical support staff and research team, users and providers). If convinced in the desired values, senior managers would commit the necessary resources to execute the analytics project and implement the analytics-based policy recommendations.

Successful organizations like e-bay, google, and amazon have adopted superior management processes by hiring analytics experts. They provide them with quality data; support them with the best analytics tools to make the best-informed decisions whether big and small, every day, over and over, (Davenport, 2006; Davenport & Patil 2012). For a recent survey on analytics models, applications, and tools we refer to Osman et al. (2014a). Further, discussion on the importance of the management process for the success of the analytics initiatives for measuring productivity performance at organizations and development of evidence-based policies can be found in Dyson (2000).

4. CAM implemenation and discusion of results

In this section, the CAM implementation processes, associated components, results and impacts are discussed. Each CAM process took almost one-year time to complete, and the project was executed over a 4-year period from 2010 to 2014. Fig. 3 depicts the data-flow chart for implementing the cognitive, analytics and management processes. The PIM (Performance Improvement Management) Software is used to generate the DEA results (Emrouznejad & Thanassoulis, 2014), while the CART analysis and visualization is generated from v6.6 (Salford Systems, San Diego-USA) software.

4.1. The implementation of the cognitive process

Turksat is a private agency entrusted to provide e-services to Turkish users. It has provided an excellent support staff to mount
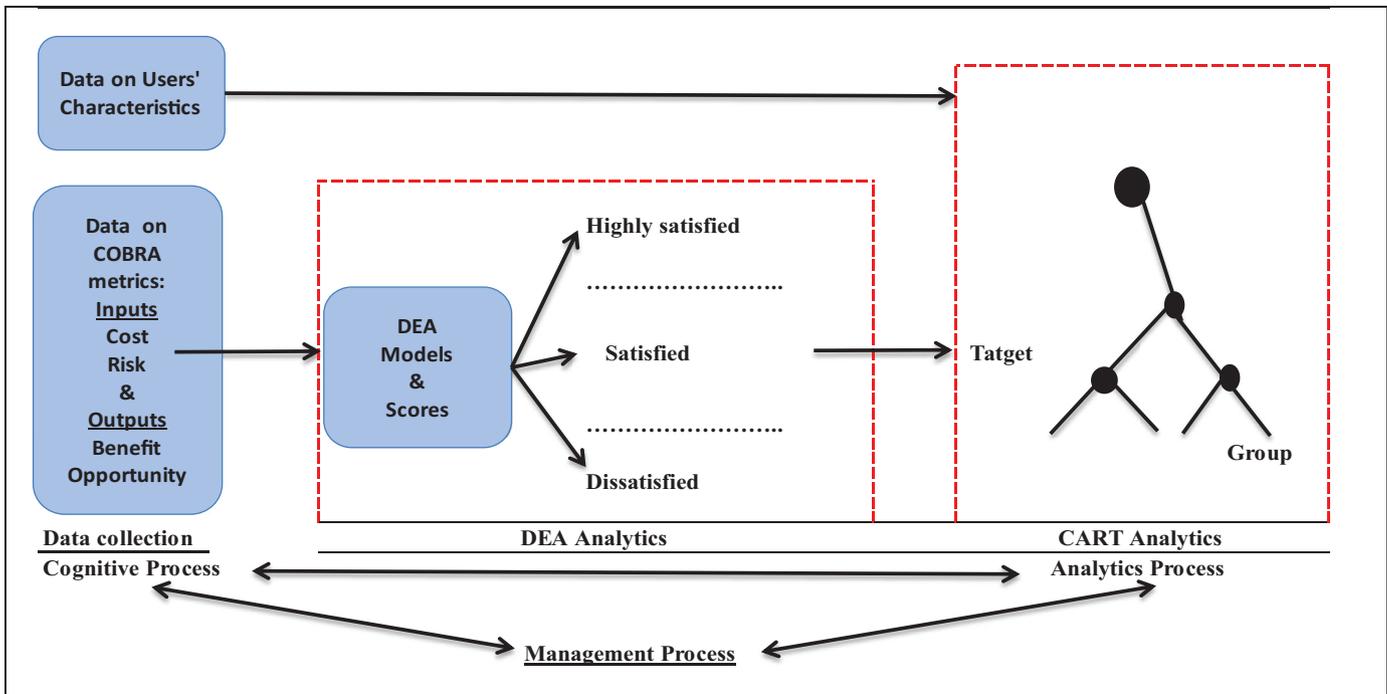
Fig. 3. The flow-chart of processes for the CAM implementation.

Table 4
List of the 13 e-services and characteristics.

Group	Code	Name	Responses
Informational-G1 (1 e-service)	9001	Content Pages for Citizen Information	2258
Interactive/Transactional-G2 (10 e-services)	860	Military Services – Application for receiving information	
	867	Online Inquiry for Consumer Complaint	
	868	Parliament Reservation for Meeting	
	871	Military Services – Deployment Place for Training	
	872	Military Services Inquiry	
	2000	Consumer Portal – Application of Consumer Complaint	636
	2002	Juridical System Portal – Citizen Entry	
	2003	Juridical System Portal – Lawyer Entry	
	2004	Juridical System Portal – Institutional Entry	
	2005	Juridical System Portal – Body of Lawyers Entry	
Personalized-G3 (2 e-services)	870	Education Service – Student Information System	284
	9000	My Personal Page	

the online survey inside the internal operating systems of e-services to collect real-experiential data from users. The online survey parts were first approved by our Universities Internal Review research boards before the data collection process took place.

4.1.1. The list of e-services

A list of 13 e-government services was selected from Turksat's e-government portal. The details on each e-service and collected responses from users are provided in Table 4. They are divided into three groups of different characteristics: (1) *informational; (2) interactive/transactional; and (3) personalized groups*. The *Informational* e-services provide public content, and do not require authentication (username and password) to access by users. *Interactive/transactional e-services,* however, do require authentication for downloading application forms, contacting agency officials and requesting appointments. Finally, *personalized e-services* also require authentication and allow users to customize the content of e-services, conduct financial transactions and pay online to receive e-services.

4.1.2. The online survey for data collection

The online survey is composed of three parts: (1) part I collects qualitative bio-data on users (education, age, income, gender, frequency of using e-government services and annual income); (2) part II accumulates quantitative data from responses of the 49 CO-BRA questions, and (3) part III gathers text-free comments in response to an open-ended question for cross-validation and content analysis. The online survey was not promoted to Turksat's users; and the data was collected using a simple random sampling process to avoid bias. After completion of an e-service interactive session, a user is invited to complete the online survey. At the start, the respondent user is informed that the personal data will be kept confidential, the collected data will only be used for an academic research to improve the provision of e-services; the user was not obliged to complete the survey and can stop any time.

The data collection process was collected over two-phases. A pilot phase collected data over a three-month period to refine the measurement scale model. The field phase was run for another period of nine months; and one dataset was gathered every three months. Since it is an unsolicited online survey, it was

Table 5
Descriptive analysis of the DEA input and output variables.

Variables	(Total number of Questions): "NO" under Column 1 of Table 2	Mean	Median	Deviation	Minimum	Maximum
DEA input variables						
tangible Cost (tC)	(7): Q20–Q21; Q30–Q31; and Q41–Q43.	22.84	25.00	8.38	7.00	35.00
intangible Cost (iC)	(6): Q44–Q49	17.19	17.00	6.93	6.00	30.00
personal Risk (pR)	(5): Q36–Q40	6.34	7.00	2.41	5.00	25.00
financial Risk (fR)	(3): Q37–Q39	9.39	10.00	3.48	3.00	15.00
DEA output variables						
tangible Benefit (tB)	(7): Q1–Q7	22.54	25.00	8.73	7.00	35.00
intangible Benefit (tB)	(11): Q8–Q18	34.84	38.00	13.22	11.00	55.00
Service support Opportunity (sO)	(5): Q19–Q22 and Q26	19.05	21.00	7.30	5.00	25.00
Technology support Opportunity (tO)	(7): Q27–Q29 and Q32–Q35	22.52	24.00	8.03	7.00	35.00

not possible to determine the termination time to accumulate enough responses. At the end of the collection period, a total of 3506 responses were collected. A data cleaning process was conducted to remove incomplete responses; a total of 3178 responses (96.64%) was found valid, and they were distributed on the list of e-services as follows: (2258 responses for the informational e-services; 636 responses for interactive/transactional e-services; and 243 responses personalized e-government services) as shown in Table 4.

Despite the fact that our analytics models are non-parametric and do not require any statistical assumptions on sample size, a sufficiency test was conducted to make sure that we have an acceptable representative sample. Given an estimate of 80 million for the Turkish population, out of which 9% are ICT users then an estimate of 7.2 million ICT users can be potential users of e-services. According to Saunders, Lewis, and Thornhill (2007), a population

of 10 million needs a sample of 2400 responses at the 95% confidence level and at 2% margin of errors. Thus our collected sample of 3178 clean responses exceeds the minimum threshold to conduct any valid statistical analysis. The respondent users were asked to rate the COBRA questions in part II on the online man–machine-interactions using 5-point Likert scale values (1 = strongly disagree, …, 5 = strongly agree).

4.1.3. Validation of COBRA measures

Further to the theoretical support for COBRA metrics provided in Section 3.1, empirical validation was also conducted to establish relationships between COBRA metrics and the satisfaction of users, and alignment to Turksat's goal. An advanced statistical structural equation model was developed in Osman et al. (2014a). The statistical results showed that the cost and risk factors have negative relationships to users' satisfaction; whereas, the benefit and

Table 6
Descriptive analysis on user's bio-data.

Variable	Ordinal Label	Attribute	Number	%Turkish	%EU27(*)
Gender	Female (F)	Female	639	20	
	Male (M)	Male	2,539	80	
Age	Low (L)	24 or less	433	15.55	**25**
		25-34	602	21.62	**39**
		35-44	704	25.28	**35**
	Middle (M)	45-54	663	23.81	**30**
	Old (O)	55 or more	383	13.75	**15**
Educational Level	Low (L)	Below High School	927	**33.32**	12
	Middle (M)	Secondary/ High School	420	15.08	28
	High (H)	Undergraduate	1,250	44.85	53
		Postgraduate/Other Qualifications	188	6.75	
Ease of e-service (Internet Experience)	Low (L)	Beginner (Less than 3 Years)	355	12.71	
	Middle (M)	Fair (3-6 Years)	570	20.50	
		Good (6- 10 Years)	944	33.90	
	High (H)	Excellent (more than 10 Years)	916	32.89	
Frequency of Use	High (H)	Daily	639	22.94	
	Middle (M)	Few times a Week	1,227	44.06	
		Few times a Month	402	14.43	
		Monthly	351	12.60	
	Low (L)	Few times a Year	166	5.96	
Annual Income	Low (L)	Less than $5000	1,152	41.36	
	Middle (M)	5000-9999	467	16.77	
		10000-19999	592	21.26	
	High (H)	20000- 29999	289	10.38	
		30000- 49999	171	6.14	
		$50000 or More	114	4.09	

* http://ec.europa.eu/eurostat/statistics-explained/index.php/File:Obtaining_information_online_from_public_authorities_by_socioeconomic_breakdown_2009.png.

opportunity factors have positive relationships to users' satisfaction. The coefficients in brackets show the values of the structural links: cost (-0.36); risk (-0.11); benefit (0.59) and opportunity (0.68) indicating that the lower the cost and the risk, and the higher the benefit and opportunity values, are, the higher the satisfaction is. The total explanation of the users' satisfaction variations by the COBRA model was 76% at the 90% confidence level.

Table 5 provides a descriptive summary of collected data on the COBRA metrics in part II. For instance, the maximum value for an aggregated set of 7 questions is 35 (7×5); and the minimum value is 7 (7×1), see the values for the set of intangible cost (tC) category. Similarly, a descriptive summary on the respondents' bio data of part I is provided in Table 6. The bio-data on users show that e-services are attracting highly educated citizen with a cumulative of 51.6% for graduate and postgraduate degree holders; this percentage is very close to the EU27 average of 53% for the same category group. It is interesting to note that the percentage of low educated users (33.32%) in Turkey is much higher than 12% of the EU27 similar group. Moreover the low age group in EU27 has a higher percentage of users than that in Turkey whereas Turkish middle and old age groups have higher values than that of EU27. Last the Eurostat 2010 shows that 28% of EU27 citizens have obtained information online from government authorities' websites in 2009 compared to only 9% in Turkey. No other EU statistics can be compared to our additional statistics generated from our survey. For instance, the frequency of e-service usages in our sample is 23% daily; 44% weekly, 27% monthly and around 6% yearly; these figures indicate a high frequency-usage level. The percentages of female and male users were 20% and 80%, respectively.

4.2. DEA prescriptive results for benchmarking analysis

Two DEA models are implemented with reported results to evaluate the satisfaction of users and the performance of e-services. First, a *local-frontier* analysis is conducted to report satisfaction and performance results on a single e-service. Second, a *meta-frontier* analysis is conducted to report overall performance and satisfaction results obtained by including all e-services in a single DEA run to identify the best-practice national benchmark which consists of the set of most efficient and effective e-services to guide the management process in the design of improved e-services.

In practice, there are operational managers and policy makers in charge of e-services. The operational managers often are interested in monitoring and controlling the operations of an e-service at the micro (local) level; hence special interest is focused on input-efficiency and output-effectiveness performance values of an e-service at the local-frontier level. The input-efficiency objective minimizes the resource (cost and risk) utilization at fixed amount of outputs. The output-effectiveness objective maximizes the (benefit and opportunity) return at fixed amount of inputs. However, the policy makers have a strategic interest in improving the performance of all e-services at the macro (Meta) level; hence the meta-frontier analysis is of interest to obtain input-efficiency and output-effectiveness values for the whole e-services sector. Hence, identification of the national best-practice benchmark is of great importance for learning and development of evidence-based policies. Therefore, input-orientation and output-orientation DEA models are used to obtain efficiency and effectiveness values at the individual level and the overall level of e-services.

Table 7 reports the averages of the DEA results without bootstrapping reported under DEA score (1) columns, while that for the bootstrapping DEA results are reported in averages of Mean (2) and Median (2) columns at both the local-frontier and meta-frontier levels. Since each DEA run provides a single DEA satisfaction score for each individual user, the average of the DEA satisfac-

Table 7
Local and meta-Frontier anlyses of satisfaction and success.

Group	e-service	Local Frontier						Meta-Frontier					
		Output-orientation			Input-orientation			Output-orientation			Input-orientation		
		DEA score (1)	Mean (2)	Median (2)	DEA score (1)	Mean (2)	Median (2)	DEA score (1)	Mean (2)	Median (2)	DEA score (1)	Mean (2)	Median (2)
G1	9001	80	78	79	67	63	63	78	78	78	69	69	68
G2	860	84	82	82	80	79	79	82	81	81	73	73	72
	867	**100**	**100**	**100**	86	84	85	**100**	**100**	**100**	80	80	79
	868	83	81	81	73	72	72	80	79	79	58	58	58
	871	80	78	78	81	80	80	73	72	72	75	75	75
	872	68	66	65	67	66	66	63	63	63	62	62	62
	2000	71	69	69	66	65	65	59	58	58	62	62	61
	2002	79	77	76	79	78	78	72	71	71	73	73	72
	2003	76	74	74	70	69	69	70	70	70	66	66	65
	2004	82	79	79	76	74	75	75	74	75	69	69	68
	2005	72	71	70	**100**	**100**	**100**	65	64	64	**100**	**100**	**100**
G3	870	80	79	79	74	73	73	77	76	76	68	68	68
	9000	82	81	81	76	74	74	79	79	79	69	69	68

1: The average of DEA scores without bootstrapping.
2: The average of DEA bootstrapping confidence intervals (mean and median) of DEA scores.
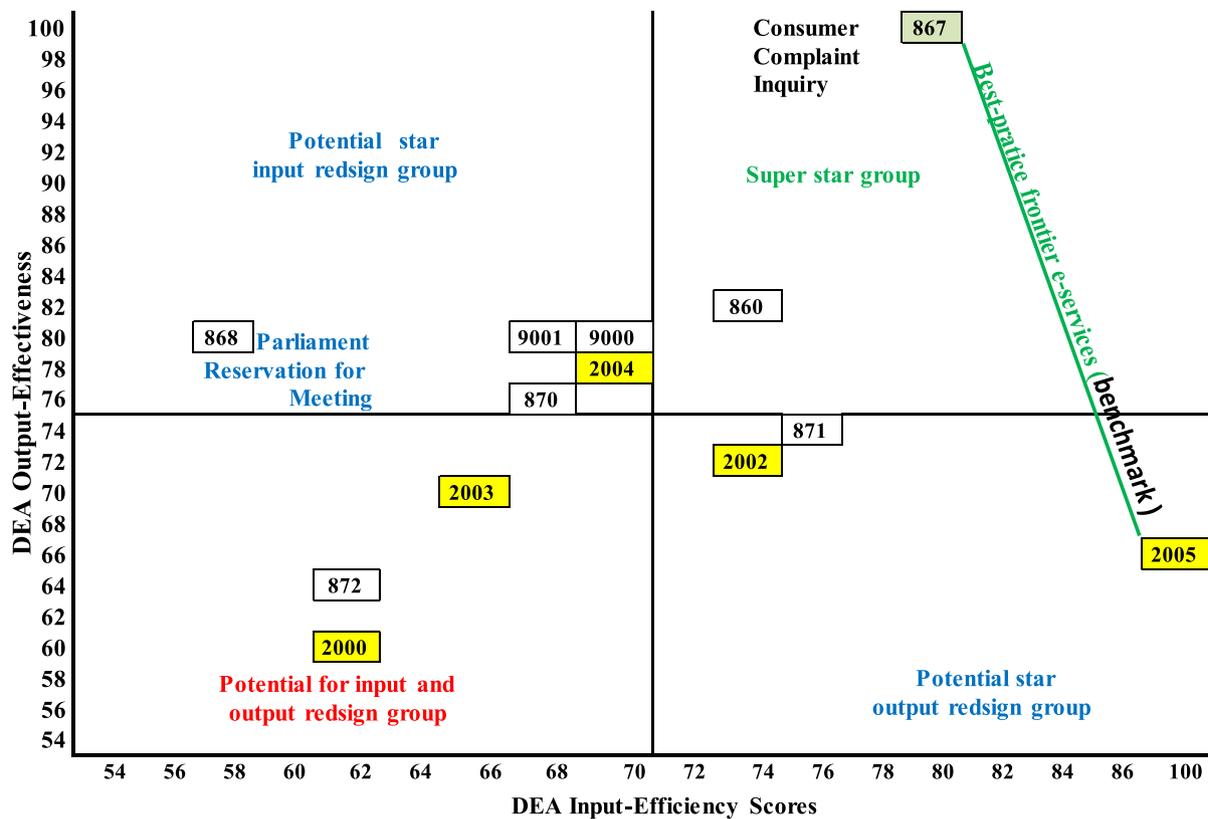
Fig. 4. The national best-practice of efficiency-effectiveness benchmarking groups.

tion scores of users is considered as a satisfaction measure for the particular e-service. The e-service satisfaction measures for a specific e-service would be different from those at the local-frontier and meta-frontier levels due to pooling of the data on all e-services in a single DEA analytics run.

From the meta-frontier analysis in Table 7, it can be seen that the best-practice national benchmark consists of the two non-dominated frontier e-services (867: online inquiry for consumer complaint; and 2005: Juridical system portal). They have either input-efficiency or output-effectiveness scores equal to 100. They envelop all other e-services under them, hence the Data Envelopment Analysis name. They provide policy makers with an identification of the best-practice e-services to recommend improvement targets to the other less efficient e-services. Additionally, plotting the averages of efficiency and efficiency pair of scores for each e-service would provide a visual representation of performances for all e-services, Fig. 4. Four different groups of e-services can be easily identified: two e-services – 2005 is input-efficient (most efficient); 867 is output-effective (most effective), they form the frontier best-practice of e-services (benchmark); whereas 860 has above average values of efficiency and effectiveness scores. 860 and 867 e-services form the *super-star* group e-services to mimic (top-right); the five e-services –868, 870, 2004, 9000, 9004 – have output-effectiveness scores above average but they are not input-efficient – a *potential star* group for input redesign (top-left): three e-services – 871, 2002, 2005 – have input-efficient scores above average but they are not output-effective - a *potential star* for output redesign (bottom right): three e-services – 872, 2000, 2003 – are neither effective input-efficient nor output-effective – a *potential* group for a complete redesign (bottom-left). The group of super star would help the policy makers in documenting their best-practice experiences to guide the learning process to improve all others inefficient e-services. It is interesting to note that the worst e-service is 2000 (Application of consumer complaint) while the best e-service is 867 (Online inquiry for consumer complaint) indicating that is easier to get an online inquiry for consumer complaint than filling an application for consumer complaint. The potential star groups include the informational e-service 9001 which attracts 71.82% of the responded users. It has an above average output-effectiveness score, i.e., providing reasonable output values to users; but it has a below average input-effectiveness score, i.e., the analysis provides transformational signals to redesign its internal process to improve the input-efficiency of such e-service by reducing its associated cost and risk factors, like Internet cost and password access costs. It is also interesting to notice that all personalized e-services (870 and 9000) belong to the output-effectiveness groups, such personalization is appreciated by users, but they have below average input-efficiency scores, i.e., such e-services should be re-designed to operate more efficiently from users' perspectives. The potential star inefficient groups contain 83% of the total number of e-services; they cut across all informational, transactional and personalized operating groups. They indicate needs for revamping the majority of e-services to improve both their efficiency and effectiveness performance levels.

To provide more analytics insights from the benchmarking analysis, the following three e-services are considered: the Juridical System Portal: Citizen Entry, (2000); Lawyer Entry (2003); Institutional Entry (2004); Body of Lawyers Entry (2005). They are designed to meet the goals and objectives of the Ministry of justice for serving its users: general public; professional lawyers, and institutional officers. From providers' perspective, they are designed to receive the same satisfaction level. However, the DEA benchmarking analysis places each e-service in different quadrants in Fig. 4 due to different performance evaluation scores from users' perspective: e-services (2000 and 2003) in bottom-left; 2004 in top-left; and e-service 2005 in the bottom-right quadrant.

Table 8
The DEA policy recommendations to improve overall performance of e-services.

Policies for COBRA metrics		Maximum	Observed	Projection	% change	Weight	Weighted change
P1: Increase benefits and opportunities (effectiveness of e-services) from users' perspective							
B	Tangible benefit	35	17.57	23.00	30.9	0.42	12.97
	Intangible benefit	55	27.85	37.09	33.2	0.15	4.98
O	Service support	30	15.13	20.15	33.2	0.14	6.48
	Technology support	35	18.63	23.61	26.7	0.28	7.47
P2: Reduce costs and risks (efficiency of e-services) from users' perspective							
C	Tangible cost	35	18.29	13.90	−24.0	0.62	−14.88
	Intangible cost	30	16.42	10.06	−38.7	0.18	−6.96
R	Personal risk	10	5.52	2.80	−49.3	0.11	−5.52
	Financial risk	15	8.51	5.08	−40.3	0.09	−3.62

Further empirical insights can be observed from the results in Table 7. First, it seems that the bootstrapping DEA was able to correct down the averages of DEA scores up to 3% at the local-frontier level and up to 1% at the meta-frontier level. At the local-frontier level, the frequency of changes (12 times) and magnitudes of corrections in the averages of the out-efficiency scores over all e-services were: 0% (once), 1% (three times) and 2% (eight times), and 3% (once); the similar changes (12 times) to the total reduction in the total averages of input-efficiency scores: 1% (eight times), 2 (three times) and 4 (once). The bootstrapping DEA results have changed equally in both models, but the largest change of 4% occurred in one of the input-oriented results, this is probably due to the existence of more correlation between to the input variables and users' characteristics than with the output variables that are more related to e-services' characteristics. Second, at the meta-frontier level, the averages of output-effectiveness values were reduced much less as follows: 0% (five times) and 1% (eight times) and the input-efficiency values were reduced by a total of 0%. The bootstrapping analysis indicates that the results at the local-frontier level are more affected by the categorical data on users' characteristics. However, it is more interesting to observe that pooling all data into a single local DEA analysis has produced no change in bootstrapping results at the meta-frontier analysis, i.e., the pooling has removed the impact of any correlation and the existence of errors. Although, the corrected changes from the bootstrapping DEA are not big in general, they may be needed for the analysis of individual e-services with a small number of responses.

Third, Table 8 suggests improvement targets to develop managerial actions to improve the e-services sector. The targets are expressed in terms of expected percentage changes on COBRA factors. At least, two general policy recommendations at the strategic level can be developed. Policy one (P1) is related to the desire to increase the benefit and opportunity values, while Policy two (P2) is related to the desire to decrease the cost and risk values. The recommended changes are computed from the difference in percentages between the desired projections and observed actual values. In Table 8, the averages of the optimal weights (weight column) for each COBRA factor are also provided. Although, they may not be unique due to the potential existence of multiple-optimality solutions for the DEA linear programming models, they can still provide an expected weighted value on the magnitude of desired changes to prioritize managerial actions. The weights are multiplied by the percentage of the recommended changes (% change column) to generate the data-driven expected magnitudes. The most important recommendations are: to reduce first the tangible cost factor; and second to increase the tangible benefit factor; and third to increase both the service and technology opportunity factors. However ignoring the order of magnitudes and using the percentage differences would favor reducing the risk factor first, followed by reducing the intangible cost factor second, and increasing the intangible benefit and service opportunity third; i.e., giving more priorities to improving the input-efficiency performance,

hence addressing the concern of users on the five e-services in the top-left quadrant of Fig. 4. The input-efficiency recommendations should be given the highest priorities since it would impact the majority of users 2542 out of 3178 (or 79.93%) of respondent users.

It should be noted that our presented recommendations are based on the projected changes using percentages from aggregated Likert scale data for the 8 measurement factors in Table 8. The aggregated data for the eight factors range from 5 to 55 Likert Scale values in Table 5. But these scales are integer ordinal scale data that are used similarly in serval studies including Cook and Zhu (2006) and Park (2010). The aggregation of Likert values would lessen the effect of the normally required continuous data type to conduct DEA sensitivity analysis. Park (2010) provided a discussion on how to interpret the DEA results with Likert scale data; it was concluded that the interpretation of recommendations for improvement in percentage of Likert scale is still possible; they should not directly operationalized in the same magnitudes of normal data; but using the underlying sprit of magnitudes. Hence, our recommendations and interpretations resemble the existing best-practice in literature, and they are implemented in the same underlying spirit of magnitude in percentage changes.

To provide further DEA recommendations at the operational level and using the above underlying spirit, one needs to extract more details on the individual metrics of each factor using the DEA local-frontier analysis for each e-service. For instance, to reduce the tangible cost and risk factors, senior management can improve the complexity of the registration process, remove the replacement of fees for lost password to access the e-services portal; provide more options to retrieve passwords; reduce the cost of Internet access, and provide more access options using public libraries and offices. Further reduction in users' intangible costs can be done through improving Internet speed, i.e., reducing the download and increasing the upload speeds. To improve tangible benefits of e-service, they can make them easier to find, easier to navigate, more interoperable and have better descriptions of links. Note that, the above recommendations are generated for variables inside each factor and were obtained from the open-ended comments.

4.3. CART analytics results

CART analysis is implemented to identify the characteristics of users who are found highly satisfied, satisfied and dissatisfied from the DEA results. The classes of users with common characteristics are generated by the CART visualization tree. The DEA analysis provides relative DEA satisfaction scores, but they do not link an individual satisfaction score to the characteristics of users. The characteristics can be identified from the set of predictors or categorical variables such as gender (male/female), or ordinal variables such education, technology experiences, frequency of use in Table 6. It is of prime importance to identify the characteristics of each social group in order to understand the underlying reasons behind the low usage. Such understanding would help in developing policy

recommendations to reduce the digital divide among social classes. Therefore, CART is implemented using DEA scores and individual characteristics to determine the common characteristics of different satisfaction classes.

To implement CART, the original DEA satisfaction scores are divided into three different groups. Since the DEA scores are numeric values between zero and 1; and a good classification requires only a finite set of ordinal values, therefore, the DEA scores are transformed into three ordinal data with one value is given to each group. If not transformed, CART would produce a complex classification tree with a large number of classes leading to a large and unrealistic number of policy recommendations. Therefore, three classification classes were created based the overall average of DEA scores and their standard deviation (μ, σ). The first group of "Satisfied, S" users includes users with DEA satisfaction scores in the interval of ($\mu \pm \sigma$) values, it has 1084 satisfied users (34.10%); the second group of "Dissatisfied, D" includes users with DEA scores are below the ($\mu - \sigma$) value; it has 1072 dissatisfied users (33.75%); and the third group of "highly satisfied, H" includes users with DEA scores are above ($\mu + \sigma$) value, it has 1022 users (32.15%). The users in each group are assigned one ordinal value of 1, 2, and 3, respectively. Looking at the distribution of DEA-scores; it is interesting to notice that the underlying distribution is not normal despite having a large sample of users; this is expected from the DEA non-parametric results, but from a practical point of view, a good success of any e-service is expected to have a normal distribution of satisfaction values. In fact, the distribution of the different satisfaction scores is almost uniformly equal and this might explain the reason for the low take-up rate.

To predict the characteristics of the 3178 responded users, the set of independent variables (predictors) in Table 6 takes categorical (male/female) or ordinal (low, medium, high) values; whereas the dependent variable (target) takes the values of 1, 2, or 3 from the individually transformed DEA scores. The CART analysis is conducted using the following settings; the Gini criterion for splitting node and a 10-fold cross-validation for learning and testing sample. In the 10-fold cross validation, the data on the 3178 users are divided into approximately 10 equal subsets which are generated by a random stratified sampling process for splitting on the set of predictors; and the construction of tree-growing process is repeated 10 times from scratch. In the cross-validation, nine subsets of the data are used for the learning sample, and one sub-set is used for the testing sample. The predictability accuracy of results was verified using two standard quality measures: Receiver Operating Characteristic (ROC) function and the Area Under Curve (AUC). ROC illustrates the trade-off values between sensitivity and specificity that could be achieved by the classification tree when varying the thresholds of the dependent variables. AUC measures the overall discrimination ability among the generated classes. The ROC and AUC values were equal to 0.86 and 0.93, respectively, indicating a high predictable accuracy of the CART constructed tree.

The CART analysis has generated a number of useful information. First, CART evaluates the splitting capability of each predictor; the most important one (frequency of use) is then assigned the highest score of 100%; the remaining predictors are relatively ranked for it, and the least predictor is found to be gender (9%) as shown in Fig. 5. Second, CART produces a detailed output, or sequences of predictors from the top of the tree to various thirteen terminal nodes (leafs). Such nodes are listed from left to right as follows: 7, 27, 18, 9, 19, 20, 11, 12, 13, 35, 36 and 24 as shown in the constructed CART of Appendix 2. Each terminal node represents one class which contains one dominant sub-group of users belonging to one of three original satisfaction groups. The dominating satisfaction sub-groups in each class are marked in bold in Table 9. Table 9 provides a summary of rich information on the classification characteristics of each class. The following points can

Table 9
CART classes based on the satisfaction of users and their characteristics.

CART classes			DEA satisfaction groups (target's transformed value)			Users' characteristics – set of predictors (categorical values)					
Class	Number of users	Leafs	%D red	%S blue	% HS green	Frequency	Age	Annual income	Education	Ease of use	Gender
1	1030	19	29.8 (307)	**41.7 (430)**	28.4(293)	L/M	L/M	–	–	–	M
2	340	18	31.5(107)	**44.1 (150)**	24.4(83)	M	M/O	M/H	L/ M	–	–
3	59	28	35.6(21)	**40.7 (24)**	23.7(14)	M	M/O	–	L/M	–	–
C-Total	1429		30.4 (435)	**42.2(604)**	27.2(390)	L3M	L3M2O	MH	2L2M		M
4	436	13	23.6 (103)	23.2(101)	**53.2 (232)**	L/H	L/M	L	–	–	–
5	147	36	25.9(38)	32.0(47)	**42.2 (62)**	H	L/M	M/H	L	–	–
6	92	24	26.1(24)	15.29 (14)	**58.7 (54)**	L	L/M	M/H	–	–	–
7	89	20	34.8(31)	22.5(20)	**42.7 (38)**	M	L/M	–	–	M/H	F
8	59	11	33.9(20)	25.4(15)	**40.7 (24)**	L/ H	O	–	–	M/H	–
C-Total	823		26.25(216)	23.94(197)	**49.81 (410)**	3L3HM	4L4MO	L2M2H	L	M/H	F
9	369	7	**47.2 (174)**	39.6(146)	13.3(49)	M	M/O	–	H	–	–
10	235	9	**39.1 (92)**	26.0 (61)	34.9(82)	M	L/M	–	–	–	–
11	199	35	**41.2 (82)**	21.6(43)	37.2(74)	H	L/M	–	H	–	–
12	72	27	**58.3 (42)**	25.0(18)	16.7(12)	M	M/O	L	L	L/M	–
13	51	12	**60.8 (31)**	29.4(15)	9.8(5)	M/H	O	–	–	L/M	–
C-Total	926		**45.46 (421)**	30.56(283)	23.97(222)	4M2H	2L4M3O	L	L2H	L/M	–

C: Class; HS: Highly Satisfied; S: Satisfied and D: Dissatisfied groups; L: Low; M: Medium and H: High.
Bold: highlights the dominant group; (x): number of users in the class.
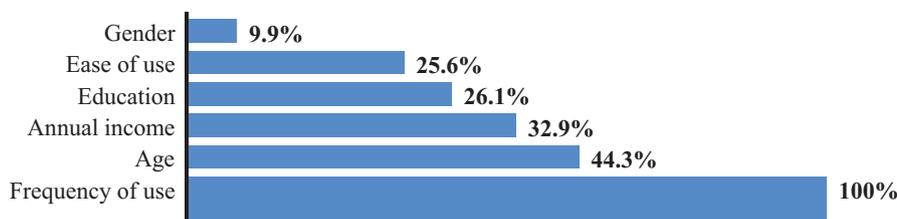
Fig. 5. Importance of predictions for each of the categorical input variables.

be observed and explained. Each satisfaction group has a unique color assigned automatically to it by CART software (Appendix 2). For instance, "Highly Satisfied, H" group is colored in green color; "Satisfied, S" is colored in blue; and "Dissatisfied, D" is colored in red. The thirteen identified different classes (1–13) with satisfaction characteristics are displayed in column 1. They are listed in a decreasing order of sizes, (the number of users) in column 2. *First*, the set of classes 1–3 explains the characteristics of majority of satisfied group of users. For instance, Class 1 (node 19 in the tree) is the largest among the set of 1–3 classes with a majority of satisfied users; it contains a set of 1030 users: 430 (41.7%) users are satisfied (S); 307 (29.8%) users are dissatisfied, and 293 (28.4%) users are highly satisfied. Further, the users of class 1 are characterized by being low (L) to medium (M) frequency of users, young (L) to middle aged users; and it is dominated by male users. If one adds the characteristics of classes 2 and 3, one would obtain the overall characteristics of a total of 1429 users: 604 (42.2% of the three lasses or 19% of the total population of 3178 users) are satisfied; the majority of them are weekly to monthly average users (3M), the majority are male between 45 and 54 years old (3M) and over (2O), middle to high income (MH), and have lower than high school (2L) and secondary education (2M).

Second the next set of 5 classes (4–8) determines the characteristics of highly satisfied users, the set contains 823 users: 410 (49.81% of the set of users, or 12.9% of the total population of 3178 users) are highly satisfied users. The largest class 4 contains 436 users (53%) who are classified to be: frequency of users – daily (H) and few times a year (L) –; less than 54 years old (L–M) and of low income (L). The general characteristics of 4–8 classes are: majority of low (3L) and high frequency users (3H); majority of less than 54 year old (4L–4M), high to middle income (2M and 2H) with lower than high school education (L), and they include a class with a majority of female users. It is interesting to note that the last two classes (7 and 8) demonstrate a fulfillment of a social e-inclusion initiative across social classes: the young (4L), middle (4M) and old (O) aged users who are average frequency users and female of low education but they are having middle to high ease of use.

Last, the set of five classes (9–13) determines the characteristics of dissatisfied users. The characteristics of the largest dissatisfied class (9) are: monthly users; above 54-year-old and highly educated. The overall characteristics for these five classes include: daily (2H) to monthly users (4M); low (L) and highly educated (2H), of all ages (2L, 4M and 3O), low income (L) and have low to medium ease of use. In general, the users are either highly educated, mature, and have a medium ease of use or low education and low income and low ease of use. The first group of high education expects more in terms of output-effectiveness, whereas the second group of low education expects more improvements in terms of input-efficiency.

It is interesting to note, CART results have highlighted a number of characteristics for each class of users; such characteristics would not have been possible to obtain from the DEA scores alone without the integration with CART. Finally, it is worth noting that the set of e-services have attracted all social classes (all ages, young to old, low to high income, male and women). Hence, the Turkish e-services are fulfilling one the EU i2010 initiative on inclusive e-government services by means of the Internet but at a low percentage of 9% of the population. Further, the above analysis provides empirical evidence indicating that the current Turkish users have additional characteristics beyond those of US adopters. In US, users were classified to be only young, better educated, and high income citizens, Morgeson, Van Amburg, and Mithas (2011).

4.4. Management process and practical impacts of policy recommendations

One of the main objectives of policy makers in Turkey was to meet the EU initiative for closing the digital divide through "improved" provision of electronic government services. The policy makers and senior managers at Turskat have played a very instrumental role in assuring success of our analytics project and implementation of its evidence-based recommendations. *First*, they approved the initiation of the project by identifying its associated challenge and desired goals, facilitated the organization of focused-group meetings, and provided the technical staff support to mount the online survey on the government portal of e-services. Hence, they provided us an excellent opportunity to identify real-time measures from users' perspective, to collect real-time quality data on the human–machine online interactions on e-services, thus avoiding data quality issues found in traditional surveys. *Second*, the senior management has also provided the executive support to implement analytics policy recommendations for achieving desired goals and creating sustainable creation of shared values. Further support to the recommendations was found from the statements of responses to the open-ended question in the survey such as "please mention other challenges and desires to improve the provision of e-services"; "the cost of registration of 10 Turkish Liras to (TL) e-government portal and the need to pay the same cost again for replacing a lost password are high"; "to add more public electronic services"; "I would like to create my personalized page on my own"; and "I wish to have the option to add the links I want to my personal page".

Combing the various analytics recommendations from the DEA input-efficiency and output-effectiveness indices and the open-ended statements has provided us with additional insights for managerial actions. The DEA and CART analyses showed that more than one third of dissatisfied users include users with distinct characteristics from all male and female groups: low income; low and highly education; low and high ease of use; medium to high frequency users. To meet their concerns, the senior management at TurkSat after communicating the recommendations to top policy makers at the Ministry of transport in charge of providing Internet services has decided to take the following set of corrective actions: (i) increased the Internet speed to reduce the time of human–machine interactions to improve both the cost and benefit factors; (ii) reduced the registration cost from 10 TL to 4 TL with more free options (email and SMS) to retrieve lost passwords, hence reducing the cost factor and contributing more to benefit

and opportunity factors; (iii) used a new architecture design to revamp all e-services in order to provide 24/7 availabilities, eliminated internal machine to machine broken links to improve interoperability among e-services; (iv) obtained ISO 9241-151 certificates for the usability and accessibility of e-services to improve opportunity factors; (v) added new eservices to provide more opportunities to users; (vi) moved the informational group (9001) to authenticated group G2 and introduced a small registration cost to the e-government portal in order to provide better opportunity in information quality; (vii) offered users more personalized e-services via social media (Blog, Twitter and Facebook accounts) using smart mobile phones with proactive reminders on the coming due date of payments, receipts and tracking options of submitted requests. The implementation of these policies led to a reduction in the cost-risk and improvement in the benefit-opportunity factors; consequently fulfilling the main goal of closing digital divide through the provision of more improved e-services to increase in the take-up rate with significant practical impacts.

Alston (2003) reported that the benefits, outcomes, impacts and shared values of e-government services to people, agencies and society have been scarce and they are often underestimated by agencies. It was noted that not all the benefits of e-government are to users, but to agencies and society as well. The study indicated that 45% of e-government users stated that they saved money by using e-government. An average savings of $14.62 per single transaction was estimated across all users; while businesses and intermediaries had higher estimates of cost savings and benefits than citizens, for instance 11% of respondents reported savings less than $10; 11% reported savings between $10 and $24; and 8% reported savings between $25 and $50 per a single interaction. The total benefits to users were estimated to be at least $1.1 billion for a population of 19.5 million citizens using a total 169 e-government programs in 2002. The government aggregate financial benefit/cost ratio across e-government programs was estimated to be 92.5% with an estimated average annual saving of $450 million.

Due to a lack of similar benefits estimates in Turkey, the above values are used to provide rough and approximate values on the Turkish benefits from the provision of new improved e-government services. Looking at the available statistics at the government portal (https://www.turkiye.gov.tr) on January 21st 2016, it can be seen that our online survey is in continuous usage at https://www.turkiye.gov.tr/anket-eu-fp7-cees), the reader can find also the following information: a total of *26,094,739* registered users out of 76,66,864 million citizens; and the development of *1394 e-services* at 211 public institutions. The above data indicates that *34.03%* of population uses e-services; it is a significant improvement over the initial value of 9% in Turkey and 28% in EU27 before starting the government transformation project in 2009. Given that the ratio of the number of registered users (26,094,739) over the whole Australian population (19,413,000 including users and non-users in 2002) has a value of 1.34, the benefits to users in Turkey can then be estimated to be $1.573 billion in 2016. The benefits to government can be similarly estimated and it mostly comes from improved business processes and service delivery, increased multi-agency cooperation, reduced service costs (advertising, printed materials, staff cost,...) as well as increased revenue. *Finally,* the wider economic and environmental benefits to society from engagement in the digital economy include reduced complexity when dealing with government, significant ease of finding information for all stakeholders, more transparent government and less corruptions; better information to make decisions; increased community skill and knowledge; more new businesses and job opportunities; more efficient supply chain management; and better opportunities to initiate partnerships between government and private sectors to deliver jointly better e-services among others.

5. Conclusions, limitation and future research

The authors have introduced a cognitive analysis management (CAM) framework to evaluate the performance of e-government services to achieve the government goal of closing the digital divide through increasing citizens' take-up rate. The CAM processes were carefully designed to model the human–machine online interactions with e-services. It advances studies on the identification of characteristics and measurable variables from users' perspective through an empirical survey. The cognitive process employed a designed online survey to capture data from users while interactions with an e-service to ensure highest level of data quality, triangulation and veracity. Much care was also employed to avoid data errors and bias found in distributed surveys. Advanced statistical tools were used to validate measures and established relationships to the organizational goal. The analytics process used DEA frontiers analytics to measure users' satisfaction as well as generating input-efficiency and out-effectiveness indices for each e-service. It established benchmarking analysis that cannot be obtained through other methods. The analytics process used the classification and regression trees for visualization and identification of characteristics of satisfied, dissatisfied and highly satisfied users. These characteristics cannot be found from the DEA results alone. The management analytics process has facilitated the synchronization and coordination among stakeholders to generate a sustainable shared value impact. Our CAM framework contributes to the OR rigor in modeling and solving complex problems while expanding the OR relevance to the excellence in practice for addressing a new challenge in a no-traditional domain of e-government, as follows:

1- Identifying a set of new holistic performance measures from the perspective of actual users. The authors believe that the presented research makes a contribution to the OR normative literature through the identification of primary measures on the performance of e-services. This is achieved using online data captured immediately after interactions. Therefore, good quality data can be assured for a proper implementation of Cost-Benefit and Risk-Opportunity Analysis.

2- Defining the human–machine online interactions as a set of decision making units (DMUs) to model and frame the evaluation of performance of e-service (machine) and satisfaction of users (human) in Data Envelopment Analysis terms is an innovative contribution of OR modeling in Government. The study has contributed to the generation of input-efficiency and out-efficiency indices to support benchmarking analysis of e-services as well as measuring users' satisfaction levels.

3- The developing of a two-dimensional visualization plot based on the input-efficiency and output-effectiveness indices for e-services, has facilitated the communication of analytics insights to non-technical managers. For instance, the set of juridical e-services was designed using the same standards. However, the DEA benchmarking analysis placed the associated four e-services in three different quadrants. Such benchmarking analysis and analytics insights were not expected from the perspective of providers.

4- Showing empirically that the DEA bootstrapping approach may not be *necessarily* needed for a large sample size.

5- Combining DEA and CART methodologies has highlighted useful information on users 'characteristics. It helped to convince policy makers to execute CAM recommendations by revamping all existing e-services and obtained the ISO quality certification.

6- Engaging senior managers at various stages of the CAM analytics processes played a significant role to assure the success of the project. Although this was not as part of a structured Delphi process, it nevertheless contributed to the evaluation and fitness of the CAM framework.

7- Measuring the outcome and impact of our CAM implementation were estimated in terms of number of users (adopters); number of new e-services; and estimated financial savings before and after the implementation of recommendations: the percentage of new users increased from 9% to 34%; number of newly designed e-services increased from few tens to over one thousands of e-services and the financial savings was roughly estimated to be over one and half billion dollars annually to users in addition to more savings to government agencies and society at large. The estimated savings would be more than fifteen billions by 2026.

8- Recommending the CAM framework for the establishment of national benchmarking indices to continuously access the development of e-services and the impact of new policy over time.

Like all studies, there are limitations which invite further research. The proposed framework was tested and validated using Likert Scale and rough estimates of the benefits and costs. CAM recommendations were implemented based on the underlying sprits of such estimates; obtaining real data would contribute to measuring the real impact of CAM implementation. Further studies on the evaluation of services should be conducted with special measures from the perspective of providers and other stakeholders to develop a 360-degree evaluation (Osman, Anouze, Hindi, Irnai, Lee, and Weerakkody, 2014b). The new studies would help to measure satisfaction and performance from all perspectives to measure different expectations among stakeholders in different countries and businesses. Last, research on block-chain technology is needed for more efficient and secure end-to-end processing capabilities; preventing fraud, increasing transparency and trust among stakeholders in the e-government ecosystem, Buchanan and Naqvi (2018).

Our CAM framework is recommended to support the Information Society Strategy of the Ministry of Development in Turkey initiative as well as other in countries to develop government performance indices, generate data-driven policies to close the digital divide and implement successfully other government transformation applications. Extension of the set of predictors to include users' physical conditions and GPS location on residential information would be advisable to provide further services to the neediest users. CAM is currently being used to assess e-services from users and providers' perspectives in UK, Qatar and Lebanon in order to modernize government services, increase e-participation, reduce corruptions, and increase transparency to achieve a sustainable growth of shared values for a smarter world.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2019.02.018.

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