Factors Influencing User Acceptance of Public Sector Big Open Data

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Abstract
In recent years Government departments and public/private organizations are becoming increasingly transparent with their data to establish the whole new paradigm of *big open data*. Increasing research interest arises from the claimed usability of big open data in improving public sector reforms, facilitating innovation, improving supplier and distribution networks and creating resilient supply chains that help improve the efficiency of public services. Despite the advantages of big open data for supply chain and operations management, there is severe shortage of empirical analyses in this field, especially with regards to its acceptance. To address this gap, in this paper we use an extended Technology Acceptance Model (TAM) to empirically examine the factors affecting users' behavioural intentions towards public sector big open data. We outline the importance of our model for operations and supply chain managers, the limitations of the study, and future research directions.

Keywords: Big Open Data, Public Sector, Use, Operations, Supply chains.

1. Introduction

In recent years there has been a redefinition of public data and the way it is being released and shared for use by different stakeholders. The value of the so-called *big open data (open data)* meets the demands of private companies and non-governmental organizations, developers and citizens; namely, the easier sharing of data across different stakeholders brings benefits that relate to its reuse for commercial purposes to public sector transparency, and decision and policy making (Vetro et al., 2016). As Hossain et al. (2016) have summarized, many current factors have led to the rising need for open data: (a) the political initiative to decentralize civic services whilst enhancing public ownership of governance activities; (b) increase in technologically aware citizens equipped with digital computing skills using their discretion in accessing, analysing and distributing information at will; and (c) the proliferation of mobile and social networking platforms (Boulton et al. 2011; Huijboom and Van den Broek 2011; Zuiderwijk et al. 2014). Additionally, the advancement of technology has made data exchange fairly simple in the digital space, turning users from mere recipients of data to functional producers and users of the same (Kulk and Van Loenen 2012). Finally, the spread of digital governance and associated norms, such as responsiveness, public services' accessibility, transparency, and accountability have triggered government initiatives to explore the wider prospective of distribution and use of such data (Sivarajah et al. 2015).

From an operations and supply chain management perspective (OSCM), the use of open data has contributed in e.g. dealing with disasters and creating resilient supply chains (Papadopoulos et al., 2016), and generating new products and services (Shadbolt et al. 2012; Rohunen et al. 2014). Furthermore, Oberg and Graham (2016) have highlighted the use of open data for supplier and distribution networks: open data from government owned traffic systems, smart parking, and smart cities in general can be used by private companies to improve their vehicle routing and transport planning, as well as improving distribution operations for perishable products (Manville et al., 2014; Oberg and Graham, 2016). In Sweden, a government-owned company is working with city planners and private companies in order to implement sensors that would manage resources such as electricity, water, traffic and waste; open data from these sensors are to be provided to organizations for the further management of their supply chains and networks (Oberg and Graham, 2016).

A scrutiny of the literature indicates that several existing studies have examined the influence of big data in OSCM settings. Wamba et al. (2015) conducted a systematic review of big data literature to synthesise the key themes and how they may impact OSCM and the business community. In another study Wamba et al. (2016) surveyed 297

Chinese IT managers and business analysts with big data and business analytic experience to examine the impact of big data on their businesses. Elsewhere, Nudurupati et al (2016) researched the influence of big data on performance management and measurement in the digital era while Duan and Xiong (2015) investigated key issues related to big data analytics and its applications to business problems. While these studies offer insights into big data and its value to OSCM, they do not expose the value created by big data to the public sector, particularly in the context of citizen-government interactions and relationship. As Wamba et el. (2015; p14) points out, "value in the context of big data implies generating economically worthy insights and/or benefits, by analysing big data through extraction and transformation". In this respect, big data can add value in a public sector context by helping to improve transparency and offering opportunities for citizens to improve their decision making through availability and access to data around issues that matter to them.

Indeed, leading countries are investing in proactive steps to improving accessibility and efficiency of big open data (machine-readability) and associated technical standards. The dedicated data.gov.uk website is a comprehensive big open data repository displaying non-personal UK government data concerning public services (including health, social services, education, transport, crime and other geo-environmental data). The intention of opening up big data relating to public services is primarily motivated by the desire to improve the operational efficiency, accountability and transparency of government (Janssen et al., 2012). Although there is significant interest and endeveours around big open data in public sectors contexts, there are several existing barriers to its adoption and use. For instance, since open data is released in raw format, it is relatively difficult for users to comprehend and use the data in a meaningful manner in a day to day decision making context (Sivarajah et al., 2015). To be capable of utilizing the full potential of big open data, users will have to acquire a certain degree of applied skills. Furthermore, although the availability of open data offers many opportunities for OSCM, there is no study in the literature that questions the usability of open data platforms, in particular, from a users' perspective. Therefore, both physical characteristics of big open data and the associated use related challenges provided the motivation for conducting this study; the aim therefore is to examine the factors that are capable of influencing user intentions towards the use of open data. By pursuing this aim, the paper contributes to existing knowledge by hypothesising factors that influence citizens' acceptance of big data in the context of their dealings with government and through developing a conceptual model to test these hypotheses. From a practical perspective the paper offers insights into factors that influence citizens' use intention regarding big open data in public sector and OSCM context and in this respect the areas big data that is open is easy to use (i.e. citizens should be able to use the data with minimum effort). This will help tackle one of the major challenges that the public sector currently faces in terms of the widening gap in citizens' engagement with digital government services (Carter and Weerakkody, 2008; Janssen et al., 2012), which not only impacts the return on investment but also the sustainability of innovations and digital services in the public sector.

The remainder of the paper is structured as follows: the next section reviews the existing literature on open data, followed by a section dedicated to the development of research model and the hypotheses proposed. The analysis and findings are presented next, whereas the paper concludes with outlining of the main contributions and limitations of this study.

2. Literature: Overview of Big Open Data

Big data is a term used to describe the volume, (amount of data created each day), velocity (how quickly data can be accumulated), and the variety of data (from multiple sources including daily transactions to social networks and daily telephone conversations) (Ahmadi et al., 2016). The availability of big open data has grown significantly and it is seen as a way to mend the traditional separation between public organizations and users (Janssen et al., 2012). "The willingness of the government to make public information that is (potentially) self-critical, or is at least perceived as unbiased, also signals to citizens that their government is functioning in a way that ultimately promotes the best interests of citizens and the society they live in" (Porumbescu, 2015; p17). For governments, it is seen as a strategy that supports and motivates public organisations to release factual, non-person specific data that has been either generated or gathered via the delivery of public services to someone with a possibility of future integration, exclusive of any copyright restrictions (Hossain et al. 2016, Bertot et al. 2014; Kassen 2013; Braunschweig et al. 2012). Increasingly, governments are imposing added pressure on all public organisations to release their raw data to the public, leading to a remarkable increase in the visibility of big open data initiatives (Janssen et al. 2012). The key factors encouraging public organisations to publish data are based on government's perception that the open access to publicly-funded data offers increased economic returns from public investment (Cranefield et al. 2014), access to policymakers in addressing complex issues (Arzberger et al. 2004), generates wealth via downstream use of outputs (Janssen et al. 2012), and increases citizen participation in analysing large datasets and challenging managers/authorities (Surowiecki 2004; Janssen et al. 2012). One of the most distinguished benefits of big open data is the increased public trust in government that allows government officials to be held accountable by the citizens (Cranefield et al. 2014; Ubaldi 2013; Janssen et al. 2012).

With open data, civil servants, citizens and other stakeholders (including private companies, supply chains and networks) can benefit from increased participation in government activities (Castellanos et al. 2013; Conradie and Choenni 2014), increased transparency and accountability (Cranefield et al. 2014), stimulating innovation (van Veenstra and van den Broek 2013). Big open data has a positive impact on economic growth; for instance, encouraging marketplace to develop products and services, which increase productivity, offer employment, and bring revenue back to the government in the form of taxation revenue (Borzacchiello and Craglia 2012 and Janssen et al. 2012). One of the societal benefits of open data also is that it allows informed and interactive citizen engagement with the government (Ubaldi 2013). Alongside the benefits are some of the challenges in using big open data, which include, upfront costs of releasing data (Cranefield et al. 2014), risk of data ownership, and privacy issues (Zuiderwijk and Janssen 2014). Two of the most significant challenges are stimulating public interest in big open data (Zuiderwijk et al. 2012; Ubaldi 2013) and poor/low data quality which government departments may be reluctant to release (Conradie and Choenni 2014; Zhang et al. 2012).

Current research on big open data is now extending beyond the organizational, systemic, and contextual effects, to also account for the push and pull effects of innovators and adopters as well as supply chains and networks (Oberg and Graham, 2016). However, there are limited studies focusing on adoption intentions of big open data (Fang and Holsapple, 2007; Wang and Senecal, 2007; Wangpipatwong et al., 2008).. Jetzek et al. (2012) develop a two by two matrix to explain value creation using social and economic values, and devise a value creation model with four propositions to be tested (Jetzek et al. 2013). Charalabidis et al. (2014) test a behavioral model to examine future usage behavior of open data users by applying TAM variables and some variables of the IS Success Model. By employing the Innovation Diffusion Theory, Estermann (2014) survey 72 respondents to explore the costs, benefits, risks and opportunities of using open data. Meijer et al. (2014) employ the public value framework to develop an open data model, which reveals that while transparency positively influences user trust in open data, privacy has a negative impact on the same. Finally, Zuiderwijk et al. (2015) have researched the acceptance and use of big open data technologies. However, to the best of our knowledge, there is no published study *empirically examining the factors affecting users' intentions to use public sector open data with a focus on OSCM, giving us the impetus for this study*.

3. Research Model and Hypotheses Development

The TAM is used in this study to examine the acceptance of public sector open data, due to its popularity in satisfactorily determining user perceptions for a system's usefulness and ease of use (Davis, 1989). This model has been recognized by many studies for satisfactorily learning and managing new technology adoption (Dillon and Morris, 1996; Park, 2009). Since the first publication of TAM, there has been a proliferation of research models including, for instance the unified theory of acceptance and use of technology (UTAUT) (e.g. Venkatesh et al., 2003) for effectively predicting user attitude and intentions towards technological innovations. It is interesting that all of these models use more or less similar constructs/attributes to measure technology adoption (Kapoor et al. 2014). Studies have reported TAM to be the superior performing model across different contexts – for instance, telemedicine adoption study by Chau and Hu (2001), study predicting general buyer behavioral intentions by Gentry and Calantone (2002), and RFID adoption study by Kapoor et al. (2014). Literature on innovation adoptions has witnessed extensive usage of TAM across the ICT sectors to elucidate user intentions towards the use of new solutions/technologies (Park et al. 2012).

It is well known that open datasets constitute many different contexts and carry varying implications. A massive group of interdependent stakeholders have differing interests in these datasets, which while being characteristically distinct are also contextually very different. Open data released to the public is currently being made available only in the raw format, which is not simple to understand. Adoption studies in the private sector have clear language and frameworks for understanding innovation adoptions (Stokes et al., 2014). Some field experts have their reservations on such frameworks and consider them to be stereotypical and without sufficient empirical evidence on the intricate nature of the innovation adoption process. On-going research is extending to account for the organizational, systemic, and contextual effects, alongside the push and pull effects of the innovators and innovation adopters. Studies like Zuiderwijk et al. (2015) explore the acceptance and use of open data technologies, but no study tests/verifies users' intentions to use big open data. There are, however, studies that have investigated the performance of different websites. For instance, Wangpipatwong et al. (2008) use the TAM Model to evaluate the use of an e-government website. Wang and Senecal (2007) employ ease of use, speed, and interactivity to measure a website's usability. Fang and Holsapple (2007) focus on the navigation structure of a website and their impact on the usability of that website by using factors defining its usability. Literature extensively supports the use of TAM constructs in measuring a new solution that is aiming to attract consumer usage based on the aspects of usefulness and ease of use (Giovanis et al. 2012; Kapoor et al. 2013; Pei et al. 2015; Prieto et al. 2014, and Sundarraj and Manochehri 2013). This enhances the appropriateness of the technology acceptance model being used in this study to evaluate user perceptions of public sector open data.

In addition to constructs from the TAM model, there is another pressing concern that requires attention whilst discussing the usage of open data by the citizens. There is a level of risk involved in using open data that the field experts have to deal with on a regular basis; this is of data being interpreted incorrectly by users, and the same data being used against the publisher (Dodds 2015). This concern can however be alleviated if the members of society, who have potentially used open data and put it to good use, willingly put in a good word about the pluses of using open data. This aspect of social approval is expected to motivate other members of the society in putting their worries to rest, and testing/using open data themselves before making the final adoption/rejection decision. TAM in this study will thereby be extended to include the component of *social approval* to account for the stereotype perception associated with the use of open data (more justification on the inclusion of this construct has been provided in section 3.3).

The impact of perceived usefulness, perceived ease of use, and social approval will thus be individually examined across users' behavioural intentions. The effect of perceived ease of use will also be studied on perceived usefulness of open data (figure 1). As suggested in the proposed model, these three characteristics are expected to significantly influence users' behavioural intentions towards the use of open data platforms. The correlations emerging from the empirical evaluations will be logically reasoned for their role in persuading citizens towards the use of open data.

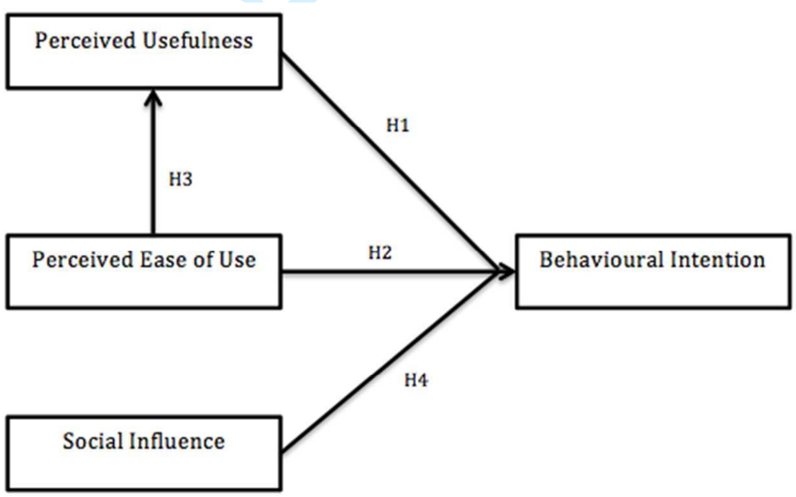

Figure 1: Modified and Extended TAM Model>

Behavioral intention, also known as use intention, is one of the most frequently used attributes in innovation related studies (Lu et al. 2008; Akturan and Tezcan 2010; Kapoor et al. 2013). Behavioral intention measures the likelihood of an individual being involved in a certain behavior (Ajzen and Fishbein 1980). As Chiu (2003) suggests, behavioral intention is an instinctive probability that consumers associate with the possibility of a particular behavior. This characteristic has also been recognized by other models of innovation adoption and diffusion (TRA and TPB) as the best immediate predictor of the actual adoption of an innovation (Ozaki 2011). The behavior of an individual, that is, their decision to accept or reject an innovative solution, is determined by their intention to perform that behavior (Fishbein and Ajzen 1975); in this case, citizens' intention to use open data. All hypotheses proposed in this study will examine the influence of the three aforementioned variables on behavioral intentions of the study's respondents.

3.1. Perceived Usefulness

Perceived usefulness is being measured to examine if the raw information available online as *big open data* is perceived by the citizens to be of relatively higher quality, in comparison to similar data that they can access using other platforms such as physical offices. In assessing the benefits of a new solution, users tend to critically evaluate the positives and negatives of using that solution or new information. Perceived Usefulness is known to determine the ultimate rate of most innovation adoptions in the long run (Pannell et al., 2006). Literature has recorded several instances where this attribute has been successfully measured for its impact on behavioral intention across numerous technologies (For example, acceptance of an online portal by Shih (2008), use of mobile Internet by Hsu et al. (2007), and so on). Unless citizens see some practical worth in big open data, they are unlikely to form positive perceptions towards its usefulness. Consistent with the theoretical principles underlying the TAM model, this study proposes that perceived usefulness would have a significant and positive impact on OSCM users' intentions to use open data. Therefore:

H1: Perceived usefulness will positively influence OSCM users' behavioural intentions towards the use of open data.

3.2. Perceived Ease of Use

Given that all of open data is released in the raw format, it is clearly not user-ready as such. Before people and businesses can use open data (severely differing in content and quality), most of it involves undergoing several layers of filtering at the legal, technical, and other stages. As witnessed, most data is negligently uploaded onto such open data websites without any clear definitions or suggestive interpretations, making it difficult for the interested stakeholders to understand and relate with the information offered over these websites (Conradie and Choenni 2014). Simple open data platforms with straightforward information are expected to enhance citizens' motivation to participate in policymaking and other governmental activities. However, the level of ease or difficulty associated with interpreting open data in the raw format will differ from person to person (Raman 2012; Martin 2014).

User knowledge of a product/service is often known to dictate individual perception of the degree of ease involved in using it. As Rogers (2003) explained, the easier a solution is to understand and implement, the faster it is accepted by the targeted users. While many studies have successfully witnessed the positive impact of this attribute on behavioural intention (for instance, Chen 2008; Sang et al. 2010), there is also a very significant relationship observed between ease of use and perceived usefulness. Many studies (Venkatesh et al. 2003; Schierz et al. 2010; Kapoor et al. 2013) support the fact that ease of using a service is often seen as a significant advantage of that service, adding to its overall usefulness. In this study, the ease of using open data websites will be examined along the aspect of optimized user experience. There is evidence in the literature that citizens and organizations refuse to rely on public sector open data based on their unfriendly user experience with open data websites; instances include failure on the part of the government to regularly update the information on such websites, and recurring problems in accessing open data (Kassen 2013). Given their raw nature, Martin (2014) concludes that open data interfaces are not user friendly, the resultant of which is limited number of users. It has been well established very early in literature that no matter how useful a new solution/service is, if it is complicated to use and understand, it will fail to attract users (Davis 1989); the resultant of which is a colossal gap between the data and its usability for the involved actor groups and stakeholders (Hunnius et al. 2014).

Based on the aforementioned arguments, the following two hypotheses have been proposed:

H2: Perceived ease of using open data will positively influence OSCM users' behavioural intentions towards its use.

H3: Perceived ease of using open data will positively influence its perceived usefulness.

3.3. Social Approval

Social approval often refers to the status gained in one's social group, as a certain non-financial characteristic of a reward, acting as the function of intention/adoption of a given innovation (Tornatzky and Klein 1982). The expected social or economic loss resulting from the application of a new solution prevents users from adopting that solution (Labay and Kinnear 1981). Observing a system often encourages peer discussions, which upon agreement leads to further encouragement towards the acceptance of that system within that discussion group (Rogers 2003). Ambiguity in raw data released on big open data platforms can cause user anxiety and uncertainty about its authenticity, which could be potentially alleviated if members of that user's social group vouch for its legitimacy. Thus, this study is interested in examining if the use of big open data is vulnerable to social influences. One of the prevalent issues today is not only that some government agencies and businesses are collecting personal information, but also that we are unaware of what is being collected. Social approval/influence, in the form of other people's recommendations and perceptions of an approved behavioral pattern is a strong determinant of adoption intentions (Mallat et al. 2006). Thus, measuring social approval will help identify both the level of awareness/exposure the OSCM users have about the use and benefits of big open data, and its role in positively driving user intentions.

H4: Social approval will positively influence OSCM users' behavioural intentions towards the use of open data.

4. Method

A national survey has been undertaken in the UK to understand the perceptions and intentions of OSCM users (including the public) towards the use of open data through this study. In analyzing the empirical data, we will be employing different statistical techniques, and Stevens (1996) proposed that for achieving precise statistical estimates and results, a study should be aiming at a sample size of over 300. Other evidences in the literature also recommend a sample size of 300 as a respectable size (Comrey and Lee, 1992). The process of gathering relevant data was outsourced to a global sampling solutions provider, SSI. This solutions company was instructed to target British citizens in their database, who have prior knowledge of open data systems and their use. The questionnaire was sent to the company, who then uploaded it onto an online survey tool. This questionnaire had one primary *dichotomous* question, where the respondents were asked if they have informed knowledge of open data systems. Only the respondents answering 'yes' to this question were allowed to continue with the rest of the questionnaire. The questionnaire also comprised of ordinal questions concerning the age group, educational qualification and income levels of the respondents.

Within a week, the survey returned 350 fully filled responses, which were then statistically analysed by the authors of this study. Questions related to the extended TAM model with four constructs (including behavioural intention) were recorded (three items/questions/statements for each). Therefore, the questionnaire for this study was designed to include 12 Likert items that had to be rated on a seven-point scale – (7) Extremely Agree (6) Quite Agree (5) Slightly Agree (4) Neutral (3) Slightly Disagree (2) Quite Disagree (1) Extremely Disagree (Appendix 2). All statements/questions were based on items that have been previously used and tested in earlier studies (Moore and Benbasat 1991; Karahanna et al. 1999; Rijsdijk and Hultink 2003; Teo and Pok 2003; Shih and Fang 2004; Richardson 2009), which were suitably modified to suit the present context of open data and its impact on citizens. The questionnaire contained a brief explanation of the concept of open data alongside information on its availability and usability.

The survey questionnaire was pretested with ten respondents, who were by profession OSCM academics, researchers, and citizens having general knowledge of open data. The test respondents agreed to fill the questionnaires and report any errors in the overall design of the questionnaire, technical correctness of the contents, or any other difficulties preventing easy understanding of the questions. At first, a five-point Likert scale was employed, but upon suggestions from the academics, a seven-point scale was introduced, as they are known to prevent respondents from being increasingly neutral with their responses, and at the same time, are also considered to be more reliable. Furthermore, each item in the questionnaire was initially numbered using shorthand of the construct being measured (for instance, Ease_Use for perceived ease of use). Academics returned with suggestions of eliminating such obvious shorthand to prevent respondents from interpreting the meaning of the construct, which could potentially influence their responses. The numbering was then changed to discreet codes to prevent respondents from falling prey to any respondent bias (for instance, Ease_Use was changed to PEOU).

In assessing the appropriateness of the items used, Grover (2011) refers to a process of *content validation*. This can be based on theory for the items used in the literature, or based on the opinions of a panel of experts, who are well learned in that domain (Grover, 2011). For this study, all items for the shortlisted constructs were defined by gathering the items utilized and confirmed by many studies of the past; that is, the items for this study were developed on the theoretical basis available for the shortlisted constructs in the existing literature (Appendix 1). This therefore confirmed the *content validation* of the instrument developed for this study. It ensured that the items forming the constructs were fully representative of them. The survey instrument was then pilot tested to confirm reliabilities of all shortlisted constructs. This test was run on 30 respondents, and care was taken to ensure that the population of the pilot test comprised of respondents from different age groups, gender, and educational backgrounds to test the suitability of the questionnaire. The data from the pilot test was tested for reliability and the alpha values for all four constructs on the reliability scale were found to be appropriate and acceptable.

5. Findings

The accumulated data was analysed using structural equation modelling (SEM) to test the proposed hypotheses by employing AMOS 21. Before undertaking SEM, the accumulated data was screened for response rates, missing cases, and potential outliers. A missing completely at random (MCAR) test was undertaken to identify missing cases and potential outliers, if any, and the nature of those missing cases to ensure their effective handling. A single test statistic checks if the cases are missing completely at random, whilst showing that the corresponding null distribution is asymptotically chi-squared (Little, 1988). The missing value analysis test was performed using the SPSS 19 statistical tool. The univariate statistics generated for the dataset showed that there were no missing cases (table 1). All 350 cases were therefore declared free of missing values. The responses, which are either inconsistent or particularly dissimilar than the rest of the dataset with extremely larger or smaller values, are referred to as outlying responses (Cho et al., 2013; Hair et al., 2010). The test for detecting univariate outliers was also undertaken using the SPSS 19 statistical tool, where the Z-scores were derived to be interpreted for the presence of probable outliers. The Z-scores for all attributes were lesser than the value of 4, suggesting there were no outlying responses (Hair et al., 2010). Therefore, the dataset was also declared free of outliers, and approved for the next stages of analyses.

Table 1: Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes[a]	
				Count	Percent	Low	High
BI1	350	4.24	1.359	0	.0	37	18
BI2	350	4.42	1.353	0	.0	28	22
BI3	350	4.52	1.405	0	.0	12	0
PE1	350	4.25	1.296	0	.0	35	19
PE2	350	4.36	1.274	0	.0	31	17
PE3	350	4.61	1.308	0	.0	26	25
PEOU1	350	4.43	1.330	0	.0	28	21
PEOU2	350	4.23	1.304	0	.0	32	20
PEOU3	350	3.98	1.504	0	.0	0	0
SA1	350	3.90	1.412	0	.0	0	0
SA2	350	4.02	1.304	0	.0	49	12
SA3	350	3.93	1.346	0	.0	14	41
a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).							

Legend: BI – Behavioral Intention; PU – Perceived Usefulness; PEOU – Perceived Ease of Use; SA – Social Approval

The dataset was also tested for non-normal distribution, whereby the Kolmogorov-Smirnov statistics, the Kurtosis, and the Skewness values were all computed to interpret the distribution type. All items for the four attributes showed Kolmogorov-Smirnov values that were statistically significant (Table 2).

Table 2: One-Sample Kolmogorov-Smirnov Test

	N	Normal Parameters		Most Extreme Differences			K-S	Sig
Items		**Mean**	**Std. Deviation**	**Absolute**	**Positive**	**Negative**		
BI1	350	4.24	1.359	0.243	0.211	-0.243	4.553	0
BI2	350	4.42	1.353	0.162	0.144	-0.162	3.027	0
BI3	350	4.52	1.405	0.153	0.15	-0.153	2.859	0
PE1	350	4.25	1.296	0.245	0.209	-0.245	4.585	0
PE2	350	4.36	1.274	0.224	0.188	-0.224	4.189	0
PE3	350	4.61	1.308	0.175	0.154	-0.175	3.278	0
EE1	350	4.43	1.33	0.197	0.18	-0.197	3.692	0
EE2	350	4.23	1.304	0.212	0.212	-0.186	3.958	0
EE3	350	3.98	1.504	0.164	0.164	-0.153	3.069	0
SA1	350	3.9	1.412	0.255	0.22	-0.255	4.766	0
SA2	350	4.02	1.304	0.262	0.233	-0.262	4.894	0
SA3	350	3.93	1.346	0.24	0.237	-0.24	4.496	0

Legend: K-S: Kolmogorov-Smirnov Statistic

Overall, 350 valid responses were gathered (table 3). The highest number of respondents (88) belonged to the 25-34 years age group, followed closely by 75 people from the 35-44 years age band. About 64 respondents were between 18 and 24 years of age, and 43 respondents fell in the 45-54 years age category. The gender distribution was found to be fairly even with 173 female respondents and slightly more number of male respondents (177 of 350). A spread of educational qualifications and annual income of the respondents has also been provided in table 3.

Table 3: Respondent Profile

Category	Values	Frequency	Percent
Age	18-24	64	18.2
	25-34	88	25.1
	35-44	75	21.4
	45-54	43	12.2
	55-64	32	9.1
	65-74	33	9.4
	Above 75	15	4.2
	Total	**350**	**100**
Gender	Male	173	49.4
	Female	177	50.5
	Total	**350**	**100**
Education	Diploma	45	12.8
	Graduate	162	46.2
	Postgraduate – Taught	76	21.7
	Postgraduate – Research	35	10
	Other	32	9.1
	Total	**350**	**100**
Annual Income	£10,000 - £25,000	55	15.7
	£26,000 - £50,000	67	19.1
	£50,000 - £100,000	179	51.1
	> £100,000	49	14
	Total	**350**	**100**

Descriptive statistics for individual items of each construct have been identified in table 4. The OSCM users rate perceived usefulness as the most important attribute, with an average mean of 4.40 (std. deviation – 1.292; variance – 1.671). Behavioral intention is considered almost equally important, with an average mean of 4.39 (std. deviation – 1.372; variance – 1.884). This is followed by perceived ease of use (Mean – 4.21; std. deviation – 1.379; variance – 1.911), and social approval receives the lowest rating with a mean of 3.95 at a std. deviation of 1.354 and variance of 1.836.

Table 4: Descriptive Statistics

Items	N	Mean	Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic
BI1	350	4.24	1.359	1.846
BI2	350	4.42	1.353	1.831
BI3	350	4.52	1.405	1.975
Average BI	**350**	**4.39**	**1.372**	**1.884**
PU1	350	4.25	1.296	1.680
PU2	350	4.36	1.274	1.623
PU3	350	4.61	1.308	1.712
Average PU	**350**	**4.40**	**1.292**	**1.671**
PEOU1	350	4.43	1.330	1.770
PEOU2	350	4.23	1.304	1.700
PEOU3	350	3.98	1.504	2.263
Average PEOU	**350**	**4.21**	**1.379**	**1.911**
SA1	350	3.90	1.412	1.995
SA2	350	4.02	1.304	1.701
SA3	350	3.93	1.346	1.812
Average SA	**350**	**3.95**	**1.354**	**1.836**

Legend: BI – Behavioral Intention; PU – Perceived Usefulness; PEOU – Perceived Ease of Use; SA – Social Approval

Cronbach's alpha is measured to establish the consistency of the attributes making up the proposed model. We tested for reliability using Cronbach's alpha (Santos 1999). All of the four constructs in the model have three items each. A reliability test is carried out on the survey instrument for this study (Table 5). Interestingly, all of the four attributes used in the model show high reliabilities (falling between 0.70 and 0.90). Moving forth, we examined the effects of perceived usefulness, perceived ease of use, and social approval on behavioral intention using structural equation modelling (SEM).

Table 5: Reliability Test

Constructs	Sample	Items	Cronbach's α	Reliability
Perceived Usefulness	350	3	.871	High
Perceived Ease of Use	350	3	.841	High
Social Approval	350	3	.880	High
Behavioural Intention	350	3	.826	High

Confirmatory Factor Analysis was undertaken to test the measurement model (Lopez-Gamero et al. 2009). The measurement model is a recursive over-identified model with a significant chi-square of 749.204 (p=0.000, df=51). The model is thus considered suitable. The model fit indices are also examined to probe into the overall model fit. The normed chi-square is reported at 2.154 (< 3), making this statistic acceptable (Kline 2005). The Root Mean Square Error of Approximation (RMSEA) is also well within the recommended limit of < 0.07 at 0.063 (Steiger 2007; Tabachnick and Fidell 2007). The Goodness of Fit Index (GFI) and the Adjusted GFI (AGFI) values are acceptably above 0.9 (0.912) and 0.8 (0.848), respectively (Gefen et al. 2000). With the incremental fit indices, Comparative Fit Index (CFI) is very close to the desired value of 0.95 at 0.957 (Gefen et al. 2000), and the Normed Fit Index (NFI) is also acceptable at 0.962 (> 0.9) (Gefen et al. 2000). Therefore, the measurement model for open data can be concluded to be of a good fit.

In discussing the discriminant and convergent validities, as already mentioned, the GFI, NFI and AGFI values are satisfactorily over the recommended values of 0.90 and 0.80, respectively. As the existing literature recommends, the chi-square value is normally expected to be statistically insignificant (Hair et al. 2006; Gefen et al. 2000; Straub et al. 2004). However, there exists an exception for larger sample sizes. The sample size of 350 for this study is considerably large, and with the other fit statistics showing good values, the significant chi-square is considered perfectly acceptable for this study (Hooper et al. 2008). In addition, the item loadings are above 0.5, with the majority being over 0.7. Also, all t-values have been reported to be acceptably significant (two-tailed at 0.001). The Average Variance Estimates (AVE) and Composite Reliability (CR) values for all latent variables have also been calculated (table 6), which are well above 0.7, as required (Fornell and Larcker 1981; Hair et al. 2010).

Table 6: AVE and CR values

Latent Variables	CR Values	BI	PEOU	PU	SA
Behavioral Intention (BI)	0.926	**0.723**			
Perceived Ease of Use (PEOU)	0.762	0.428	**0.589**		
Perceived Usefulness (PU)	0.739	0.261	0.521	**0.534**	
Social Approval (SA)	0.714	0.221	0.429	0.332	**0.521**

Legend: CR – Composite Reliability; Values in **bold** – AVE Values; Others – Squared Correlations

The diagonal in the matrix (table 6) shows that all AVE values are satisfactorily above 0.5. The values below this diagonal are the squared correlations for the represented pair of latent variables. The paired correlations are lower than their corresponding AVE values, which positively favor the model. With this, all conditions for confirming the discriminant and convergent validities are satisfied, confirming the overall construct validity for the open data measurement model.

Having established the construct validities, the latent variables were tested for any common method variance. In doing so, the *Harman's single factor test* was employed, whereby the *principal component analysis* (PCA) was performed. The results of this test showed that no single variable accounted for majority of the variance (table 7), that is, more than 50% (Harman, 1976; Podsakoff et al., 2003). The value reported for the proposed model reported a variance of 48.43%, within the 50% mark, indicating there was no common method bias in the dataset for this study.

Table 7: Principal Component Analysis

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	5.812	48.437	48.437	5.812	48.437	48.437
2	2.085	17.372	65.809			
3	.855	7.125	72.933			
4	.642	5.348	78.282			
5	.565	4.707	82.988			
6	.424	3.536	86.525			
7	.352	2.937	89.462			
8	.292	2.429	91.892			
9	.281	2.344	94.236			
10	.245	2.046	96.281			
11	.228	1.899	98.181			
12	.218	1.819	100.000			
Extraction Method: Principal Component Analysis.						

The hypothesized relationships are next introduced between the latent variables in the measurement model. The fit statistics for the structural model (figure 2) have been recorded in table 8.

Table 8: Statistical estimates for the Structural Model

Independent and Dependent Variable Relationships		**Estimates**		
Independent Variables	Dependent Variables	β	C.R.	P
Perceived Usefulness	Behavioral Intention	0.68	3.705	0.002
Perceived Ease of Use	Behavioral Intention	0.18	2.293	0.000
Social Approval	Behavioral Intention	0.29	2.733	0.008
Perceived Ease of Use	Perceived Usefulness	0.36	3.423	0.000
R-Square for Perceived Usefulness		0.49		

R-Square for Behavioral Intention	0.58
Chi-Square (χ^2)	845.404
Probability Level	0.000
Degrees of Freedom	54
CMIN/df (χ^2/df)	2.459
Comparative Fit Index, CFI	0.953
Goodness of Fit, GFI	0.940
Adjusted Goodness of Fit, AGFI	0.803
Normed Fit Index, NFI	0.987
Root Mean Square Error of Approximation, RMSEA	0.058
Sample Size	350

Four hypotheses were established for examining the acceptance of big open data in the public sector. All of the four hypotheses are supported by the gathered data (H1, H2, H3, and H4). The chi-square value for this model is reported significant at 845.404 (p=0.000) with 54 degrees of freedom. The other fit indices were also examined, and it was found that the CFI (0.953>0.95), GFI (0.940>0.9), AGFI (0.803>0.8), and RMSEA (0.058<0.070) values are all well aligned with their recommended values. The CMIN/df value at 2.459 is also well below 3. The NFI value is above 0.9 at 0.987. Again, fit statistics meet their recommended values, and a big sample size (n=350) used for this SEM, makes the significant chi-square of 845.404 acceptable for this model. Alike the measurement model, the structural model for open data also displays a good model fit.

Table 8 shows that this model has two endogenous and three exogenous latent variables. Of the two endogenous variables, *behavioral intention*, explains 58% variance (SMC=0.58) and *perceived usefulness* explains 49% variance (SMC=0.49). Straub et al. (2004) suggest 0.40 and above to be the acceptable adjusted R^2 value, therefore, the SMC values reported herein are contributing towards an acceptable level of predictability for the structural model used in this study. It is clear from the SEM results that perceived usefulness (Beta= 0.68, p= .002) is the strongest predictor of citizens' intentions to use open data, and perceived ease of use is a good predictor of the usefulness of open data (Beta= 0.36, p= .000).

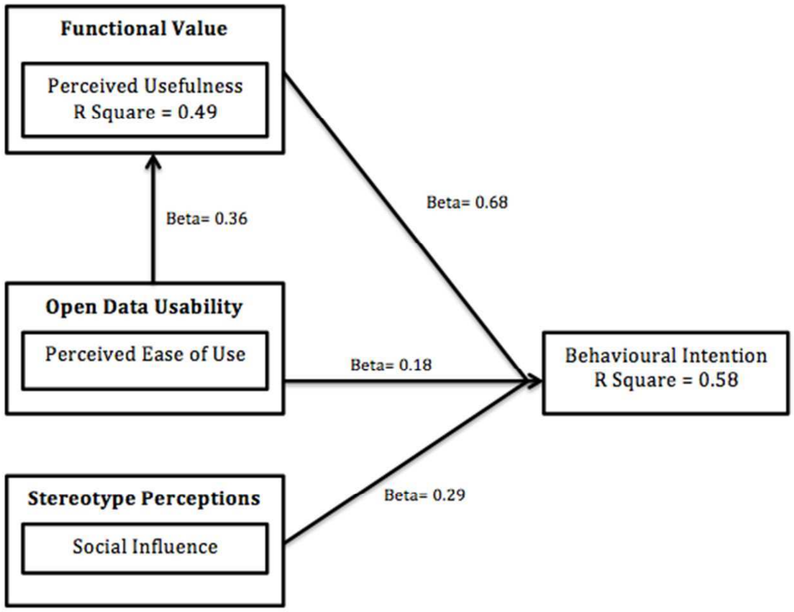

Figure 2: Validated Research Model

The functional value of open data is measured using perceived usefulness (figure 2). In rating the perceived usefulness of open data, about 45% respondents were neutral about the opinion that open data is useful in making day-to-day decisions (PU1). With most people again being neutral, about 25% people slightly agreed that open data helped them make better decisions (PU2, table 9). While 30% respondents were neutral about the idea, 55% agreed that open data helped their understanding of governmental actions that directly affect them as citizens (PU3).

Table 9: Frequencies for Perceived Usefulness

Perceived Usefulness	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
PU1	13	22	27	159	78	32	19
PU2	10	21	27	144	89	42	17
PU3	8	18	25	106	113	55	25

About 38% respondents were neutral about open data being easy to use (PEOU1). Then there were 19% respondents who slightly agreed on open data websites being challenging and frustrating to use (PEOU2). While 29% believed that their understanding of open data was very clear, 32% were neutral with their opinion of it, and 30% denied the same (PEOU3, table 10).

Table 10: Frequencies for Perceived Ease of Use

Perceived Ease of Use	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
PEOU1	11	17	34	132	83	52	21
PEOU2	6	26	54	139	67	38	20
PEOU3	18	43	62	111	55	42	19

With most people being neutral about people important to them recommending the use of open data (47%), 25% had social approval on using open data (SA1). While 28% respondents had their friends, family, and colleagues support their use of open data, an almost equal proportion of respondents (23%) denied any such support from their social circle (SA2). With almost half of the respondent population being neutral about the statement – people who influence my behaviour think I should use open data, 24% agreed to the same (SA3, table 11).

Table 11: Frequencies for Social Approval

Social Approval	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
SA1	20	49	27	166	40	35	13
SA2	15	34	32	173	51	33	12
SA3	14	42	42	167	44	23	18

In rating the responses for items related to behavioural intentions, about 36% respondents planned to use open data, as they believed that the central idea of such data is to create transparency within a democracy (BI1). A good percentage of respondents (48%) said that despite them being aware of the benefits of open data, their personal willingness to use open data is not high (BI2). Again, with 30% respondents being neutral of the use of open data, about 49% said that the likelihood of them using open data was not very high (BI3, table 12).

Table 12: Frequencies for Behavioural Intention

Behavioural Intention	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
BI1	18	19	28	159	65	43	18
BI2	10	18	48	107	96	49	22
BI3	12	13	46	106	83	63	27

6. Discussion and implications

6.1 Theoretical contribution

Numerous studies have employed TAM in investigating users' intentions towards the acceptance of a given solution or service (Park et al. 2012). Behavioural intention is considered the intuitive likelihood that a user directly relates with the probability of performing/displaying certain behaviour (Chiu 2003). Most models unanimously recognize behavioural intention as the best predictor of user behaviour (Lee and Rao 2009; Ozaki 2011). A total of four hypotheses were examined to determine the effects of three predictor variables (perceived usefulness, perceived ease of use, and social approval) of this study on users' behavioural intentions (H1, H2, H4), and their perceptions of usefulness of open data (H3). Our findings suggest that users still have their doubts about the level of transparency in open data and the degree of corruption in government functions (O'Hara 2011) with respondents showing limited willingness to use open data (see table 8). With almost half of the respondent population not being certain of the advantages of open data and its importance in their everyday life (section 5, table 5), it is quite evident that users lack knowledge and exposure on the subject. Before they can harness the benefits of open data, they have to be educated on the usefulness of this data being released by the government, which is mostly in their interest and give them the opportunity of being involved in policymaking and governmental decision making.

Innovation adoption studies consider perceived usefulness a very strong determinant of favourable use intentions. The governing idea behind open data and platforms offering such data is to make it simpler for citizens to gain access to some of the government data, which is expected to facilitate civic engagement in government decisions (Martín et al. 2015). By releasing such information, government enables citizens to see the usefulness of this data in increasing transparency in government functions, and also invites their participation in future policymaking decisions that would directly affect them on a daily basis (Conradie and Choenni 2014; Janssen et al. 2012). As proposed in hypothesis H1 of this study, this study confirms a positive and significant impact of *perceived usefulness* on *behavioural intentions* of the open data users. With H1 being supported by the data gathered in this study, it can be stated that UK users have positive ideas regarding the usefulness of public sector open data. This behaviour of perceived usefulness is also backed by earlier studies across different technologies (Purnawirawan et al. 2012; Liaw and Huang 2013; Hess et al. 2014).

As already emphasized in the paper, open data released in raw format comes with the drawback of limited understanding and interpretation. From the government perspective, one of their motives behind releasing big open data is to encourage technically skilled users to use this data for designing and developing creative applications, supply networks, improving operations and supply chains, and providing tools to engage and serve the wider community - citizens, businesses, public sector organizations, and independent developers (Martín et al. 2015; Kassen 2013; Oberg and Graham, 2016). As hypothesised in H2 and H3, this study confirms the positive and significant influences of both *perceived ease of use* on *behavioural intentions* and *perceived ease of using open data* on its *perceived usefulness*. The significance of these two relationships has been massively supported by previous studies under varying contexts including, for instance, IT acceptance (Kim et al., 2009). This result bodes well for public sector institutions who wish to make their data open to the public, but also offers insights into the importance of ensuring that any big data that is open is easy to use (i.e. citizens should be able to use the data with minimum effort). This will help tackle one of the major challenges that the public sector currently faces in terms of the widening gap in citizens' engagement with digital government services (Carter and Weerakkody, 2008; Janssen et al., 2012), which not only impacts the return on investment but also the sustainability of innovations and digital services in the public sector.

The quality of information available on the Internet is open to manipulation, and hence questionable in terms of its reliability (Hand 2012). With big open data available for anyone to build applications, there are possibilities for human errors leading thereby to wrong decisions on the basis of incorrect information available in the form of open data. However, early adoption of a solution in a member's social circle has the potential to trigger a bandwagon effect (Abrahamson and Rosenkopf 1997). If members of a social group who have tried and tested open data vouch for its usefulness, it will be perceived as a form of social approval by the other members of the system, with them in turn forming positive intentions of employing open data in their future decisions. Information exchange and social interaction play a massive role in promoting innovation adoption (Bandura 1986). In addressing the stereotype perception for this study, hypothesis H4 was supported by the gathered data, with a positive and significant effect of *social approval* being recorded on OSCM users' behavioural intentions to use open data. Social approval is regarded as one of the components of perceived usefulness (Moore and Benbasat 1991). This component measures the degree to which the members of a social system approve the usage of a certain product/service (Lopez-Nicolas et al. 2008). Many studies in the literature have confirmed positive results of social approval on user intentions (Shin, 2010; Claudy et al., 2011; Lee et al., 2011).

6.2 Managerial implications

Local and central governing departments have made open data one of their priorities; conceptualizing its usefulness from a user's standpoint offers new insights to policymakers and researchers for efficiently tackling the spread and use of public sector big open data in the UK. It is well known that currently, open data is being regarded highly within the administrative and management structures in the UK, and yet the literature has no evidence/record of a conceptual model or instrument that can be used to assess the willingness and intentions of users towards open data. . The value of big open data in a public sector context will only be realised if it contributes to improving transparency, trust and decision making capabilities of citizens who will use it (Sivarajah et al., 2015; Janssen et al., 2012). Therefore, understanding how citizens perceive big open data and their willingness to accept it is vital for policy makers and practitioners engaged in developing and releasing big data repositories in a public sector context. In this respect, the research model proposed and validated in this study can thus be used as a normative source for understanding user perceptions of public sector open data.

The findings presented in this paper can be used by the digital government policymakers and practitioners in the UK as well as from operations and supply chain managers to gain first-hand knowledge of understanding of big open data. Insights from the study can be used to motivate more government institutions to develop useful and easy to use big open data repositories as part of their digital government strategy; this can facilitate the improved engagement of citizens in public sector decision making processes and contribute towards improving the efficiency of public services. Also, the conclusions from this study can be used as a base reference to build up on an extensive international model/study, where their significance and validity can be evaluated for scalability. The findings from this study clearly suggest that OSCM users are interested in incorporating open data, if there is evidence of it being useful and more insightful in comparison to other data forms, and also, importantly, if it is easy to understand and use.

The government initiatives promoting open data to bring about transparency in government functions appear to be a success, particularly with current users approving the usefulness of this data in encouraging the members of their social group to use open data. As also revealed in this study, the percentage of users forming positive use intentions is not high. This calls for continued efforts from the government and operations and supply chain managers in ensuring that meaningful and easily interpretable data with clear benefits reaches the users to achieve high/intended number of open data users.

7. Conclusions, limitations and future research directions

Studying available literature and reviewing the secondary information on open data suggests that public sector open data is being released in the best interest of citizens and business communities. The manner in which stakeholders access and use open data is governed by the manner in which such data is published (Braunschweig et al. 2012). However, a good look at the open data resources and platforms reveals that all of the released information is in the form of raw data files. This information is very poorly structured, often with overlapping contexts, being of no potential use to a layman without sound technical knowledge. Such confusing information results in loss of citizen interest in such open data platforms, with the potential impact of open data remaining unexplored.

Clearly, one of the biggest challenges for big open data publishers is making it come to life, and hence the conscious efforts in encouraging skilled users to reorganize existing data to offer useful visualizations for the end users (Data gov, 2016). Governing bodies releasing such data expect technically equipped users (software developers and coding experts) to exploit the released data in its raw format and develop meaningful applications and tools for the benefit of the society (Data gov, 2016). The output of this exercise is expected to be simplified and orderly grouping of raw data for it to be usable by the public, for instance – (a) to undertake comparative analysis of trends across different policy areas over time; and/or (b) gain a general understanding of different government functions.

Despite continued governmental initiatives through hackathons, workshops and conferences, there limited, if any, information on the factors governing user perceptions and intentions to use open data technologies. In this study, two attributes from the TAM model alongside social approval are aimed at exploring different aspects spread across – the functional value of big open data (perceived usefulness), its usability (perceived ease of use), and a stereotype perception associated with its use (social approval). SEM undertaken for this study with its empirical findings suggests that *perceived usefulness of open data* is the strongest predictor of OSCM users' *behavioural intention* towards its potential use. Also, *perceived ease of use* and *social approval* positively and significantly predict behavioural intentions of the users towards the use of open data. To further add, an additional relationship between perceived usefulness and perceived ease of use showed a positive influence of the latter over the former. Implicitly, this suggests that users find easy to use open data as one of its advantages, thereby resulting in them forming positive intentions about the usefulness of public sector open data in their everyday lives.

In acknowledging the limitations of this study the following points have been identified. Public sector open data is still in its nascent stage, and given its raw data format, its relevance and benefits are limited. This only allowed the study to examine the constructs for their influence on intention to use open data, and not on the actual adoption of open data. This study intends to extend it findings at a future point in time for the adoption aspect of open data; with strategies in place, open data is soon expected to reach more number of users, particularly, the data from local governments and local services which will be of direct relevance to the public. Although the survey company was instructed to gather data from users having prior knowledge of open data, the survey results showed significant percentage of neutral responses (see tables 5, 6, 7, and 8). Future research will target a more focussed set of respondents, with them having considerable knowledge and genuine experience of open data usage; this will ensure the survey outcome are truly user oriented. With only three constructs (TAM) examined within this study, the future aim is to study the role of other adoption factors (such as compatibility, observability, visibility, result demonstrability, image and so on) and their effects on user intentions to use open data. Finally, the authors of this paper also intend to determine how big open data can contribute to improved life quality whilst fostering innovative, sustainable digital solutions and services in the public sector.

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Appendix 1: Shortlisted constructs and sources

Constructs	Source(s)
Behavioral Intention	Karahanna et al (1999); Teo and Pok (2003); Shih and Fang (2004);
Perceived Usefulness	Moore and Benbasat (1991); Shih (2008); Hsu et al. (2007)
Perceived ease of use	Moore and Benbasat (1991); Shih and Fang (2004); Yang et al (2006); Chen 2008; Richardson (2009); Sang et al. 2010
Social Approval	Mallat et al. 2006; Dwivedi and Irani (2009); Claudy et al (2011); Ozaki (2011)

Appendix 2: Likert Scale Items

BI1: I plan to use open data, as the central idea of open data is to create transparency within a democracy
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

BI2: Despite the known benefits of open data, my personal willingness to use open data is not high
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

BI3: My willingness to use open data is not very high
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PU1: I find open data useful in making day-to-day decisions
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PU2: Using open data helps me make better decisions
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PU3: Open data helps me better understand government actions that directly affect me as a citizen
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PEOU1: Open data will be easy to use for me
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PEOU2: I believe that using open data websites is challenging and frustrating
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PEOU3: My understanding of open data is very clear
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

SA1: People important to me think I should use open data
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

SA2: My family, friends & colleagues support the use open data

☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

SA3: People who influence my behavior think I should use open data
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

Table 1: Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes[a]	
				Count	Percent	Low	High
BI1	350	4.24	1.359	0	.0	37	18
BI2	350	4.42	1.353	0	.0	28	22
BI3	350	4.52	1.405	0	.0	12	0
PE1	350	4.25	1.296	0	.0	35	19
PE2	350	4.36	1.274	0	.0	31	17
PE3	350	4.61	1.308	0	.0	26	25
PEOU 1	350	4.43	1.330	0	.0	28	21
PEOU 2	350	4.23	1.304	0	.0	32	20
PEOU 3	350	3.98	1.504	0	.0	0	0
SA1	350	3.90	1.412	0	.0	0	0
SA2	350	4.02	1.304	0	.0	49	12
SA3	350	3.93	1.346	0	.0	14	41

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

Legend: BI – Behavioral Intention; PU – Perceived Usefulness; PEOU – Perceived Ease of Use; SA – Social Approval

Table 2: One-Sample Kolmogorov-Smirnov Test

	N	Normal Parameters		Most Extreme Differences			K-S	Sig
Items		Mean	Std. Deviation	Absolute	Positive	Negative		
BI1	350	4.24	1.359	0.243	0.211	-0.243	4.553	0
BI2	350	4.42	1.353	0.162	0.144	-0.162	3.027	0
BI3	350	4.52	1.405	0.153	0.15	-0.153	2.859	0
PE1	350	4.25	1.296	0.245	0.209	-0.245	4.585	0
PE2	350	4.36	1.274	0.224	0.188	-0.224	4.189	0
PE3	350	4.61	1.308	0.175	0.154	-0.175	3.278	0
EE1	350	4.43	1.33	0.197	0.18	-0.197	3.692	0
EE2	350	4.23	1.304	0.212	0.212	-0.186	3.958	0
EE3	350	3.98	1.504	0.164	0.164	-0.153	3.069	0
SA1	350	3.9	1.412	0.255	0.22	-0.255	4.766	0
SA2	350	4.02	1.304	0.262	0.233	-0.262	4.894	0
SA3	350	3.93	1.346	0.24	0.237	-0.24	4.496	0

Legend: K-S: Kolmogorov-Smirnov Statistic

Table 3: Respondent Profile

Category	Values	Frequency	Percent
Age	18-24	64	18.2
	25-34	88	25.1
	35-44	75	21.4
	45-54	43	12.2
	55-64	32	9.1
	65-74	33	9.4
	Above 75	15	4.2
	Total	**350**	**100**
Gender	Male	173	49.4
	Female	177	50.5
	Total	**350**	**100**
Education	Diploma	45	12.8
	Graduate	162	46.2
	Postgraduate – Taught	76	21.7
	Postgraduate – Research	35	10
	Other	32	9.1
	Total	**350**	**100**
Annual Income	£10,000 - £25,000	55	15.7
	£26,000 - £50,000	67	19.1
	£50,000 - £100,000	179	51.1
	> £100,000	49	14
	Total	**350**	**100**

Table 4: Descriptive Statistics

Items	N	Mean	Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic
BI1	350	4.24	1.359	1.846
BI2	350	4.42	1.353	1.831
BI3	350	4.52	1.405	1.975
Average BI	**350**	**4.39**	**1.372**	**1.884**
PU1	350	4.25	1.296	1.680
PU2	350	4.36	1.274	1.623
PU3	350	4.61	1.308	1.712
Average PU	**350**	**4.40**	**1.292**	**1.671**
PEOU1	350	4.43	1.330	1.770
PEOU2	350	4.23	1.304	1.700
PEOU3	350	3.98	1.504	2.263
Average PEOU	**350**	**4.21**	**1.379**	**1.911**
SA1	350	3.90	1.412	1.995
SA2	350	4.02	1.304	1.701
SA3	350	3.93	1.346	1.812
Average SA	**350**	**3.95**	**1.354**	**1.836**

Legend: BI – Behavioral Intention; PU – Perceived Usefulness; PEOU – Perceived Ease of Use; SA – Social Approval

Table 5: Reliability Test

Constructs	Sample	Items	Cronbach's α	Reliability
Perceived Usefulness	350	3	.871	High
Perceived Ease of Use	350	3	.841	High
Social Approval	350	3	.880	High
Behavioural Intention	350	3	.826	High

Table 6: AVE and CR values

Latent Variables	CR Values	BI	PEOU	PU	SA
Behavioral Intention (BI)	0.926	**0.723**			
Perceived Ease of Use (PEOU)	0.762	0.428	**0.589**		
Perceived Usefulness (PU)	0.739	0.261	0.521	**0.534**	
Social Approval (SA)	0.714	0.221	0.429	0.332	**0.521**

Legend: CR – Composite Reliability; Values in **bold** – AVE Values; Others – Squared Correlations

Table 7: Principal Component Analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.812	48.437	48.437	5.812	48.437	48.437
2	2.085	17.372	65.809			
3	.855	7.125	72.933			
4	.642	5.348	78.282			
5	.565	4.707	82.988			
6	.424	3.536	86.525			
7	.352	2.937	89.462			
8	.292	2.429	91.892			
9	.281	2.344	94.236			
10	.245	2.046	96.281			
11	.228	1.899	98.181			
12	.218	1.819	100.000			
Extraction Method: Principal Component Analysis.						

Table 8: Statistical estimates for the Structural Model

Independent and Dependent Variable Relationships		Estimates		
Independent Variables	Dependent Variables	β	C.R.	P
Perceived Usefulness	Behavioral Intention	0.68	3.705	0.002
Perceived Ease of Use	Behavioral Intention	0.18	2.293	0.000
Social Approval	Behavioral Intention	0.29	2.733	0.008
Perceived Ease of Use	Perceived Usefulness	0.36	3.423	0.000
R-Square for Perceived Usefulness		0.49		
R-Square for Behavioral Intention		0.58		
Chi-Square (χ^2)		845.404		
Probability Level		0.000		
Degrees of Freedom		54		
CMIN/df (χ^2/df)		2.459		
Comparative Fit Index, CFI		0.953		
Goodness of Fit, GFI		0.940		
Adjusted Goodness of Fit, AGFI		0.803		
Normed Fit Index, NFI		0.987		
Root Mean Square Error of Approximation, RMSEA		0.058		
Sample Size		350		

Table 9: Frequencies for Perceived Usefulness

Perceived Usefulness	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
PU1	13	22	27	159	78	32	19
PU2	10	21	27	144	89	42	17
PU3	8	18	25	106	113	55	25

Table 10: Frequencies for Perceived Ease of Use

Perceived Ease of Use	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
PEOU1	11	17	34	132	83	52	21
PEOU2	6	26	54	139	67	38	20
PEOU3	18	43	62	111	55	42	19

Table 11: Frequencies for Social Approval

Social Approval	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
SA1	20	49	27	166	40	35	13
SA2	15	34	32	173	51	33	12
SA3	14	42	42	167	44	23	18

Table 12: Frequencies for Behavioural Intention

Behavioural Intention	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
BI1	18	19	28	159	65	43	18
BI2	10	18	48	107	96	49	22
BI3	12	13	46	106	83	63	27

List of Figures

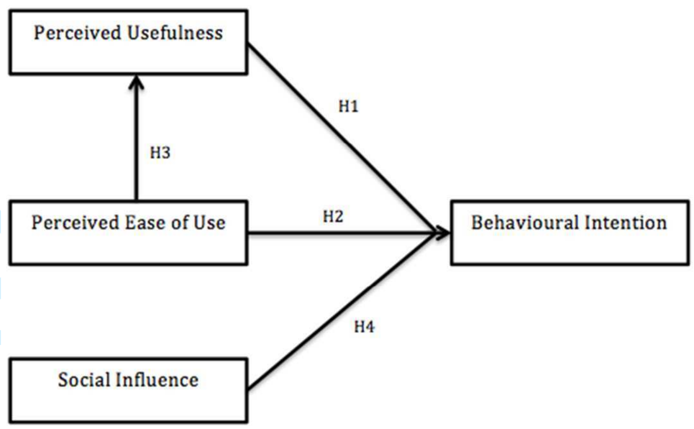

Figure 1: Modified and Extended TAM Model

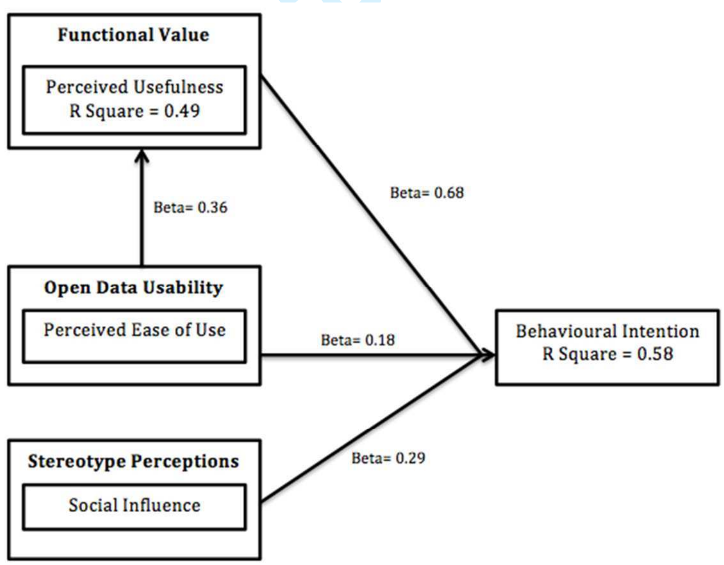

Figure 2: Validated Research Model

List of Figures

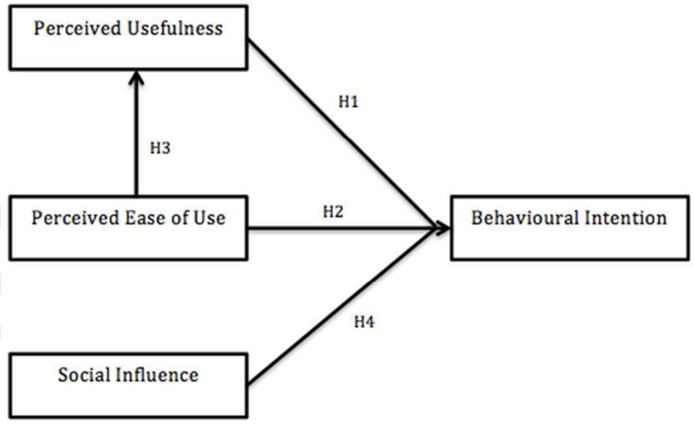

Figure 1: Modified and Extended TAM Model

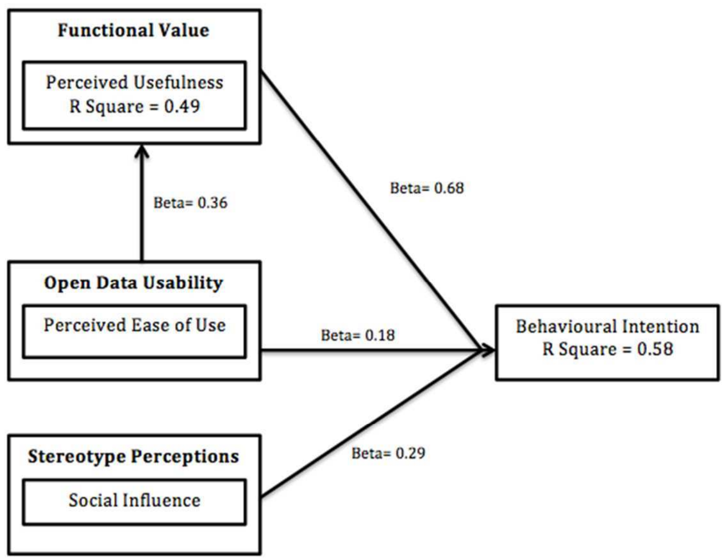

Figure 2: Validated Research Model

Table 1: Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes[a]	
				Count	Percent	Low	High
BI1	350	4.24	1.359	0	.0	37	18
BI2	350	4.42	1.353	0	.0	28	22
BI3	350	4.52	1.405	0	.0	12	0
PE1	350	4.25	1.296	0	.0	35	19
PE2	350	4.36	1.274	0	.0	31	17
PE3	350	4.61	1.308	0	.0	26	25
PEOU1	350	4.43	1.330	0	.0	28	21
PEOU2	350	4.23	1.304	0	.0	32	20
PEOU3	350	3.98	1.504	0	.0	0	0
SA1	350	3.90	1.412	0	.0	0	0
SA2	350	4.02	1.304	0	.0	49	12
SA3	350	3.93	1.346	0	.0	14	41

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

Legend: BI – Behavioral Intention; PU – Perceived Usefulness; PEOU – Perceived Ease of Use; SA – Social Approval

Table 2: One-Sample Kolmogorov-Smirnov Test

	N	Normal Parameters		Most Extreme Differences			K-S	Sig
Items		**Mean**	**Std. Deviation**	**Absolute**	**Positive**	**Negative**		
BI1	350	4.24	1.359	0.243	0.211	-0.243	4.553	0
BI2	350	4.42	1.353	0.162	0.144	-0.162	3.027	0
BI3	350	4.52	1.405	0.153	0.15	-0.153	2.859	0
PE1	350	4.25	1.296	0.245	0.209	-0.245	4.585	0
PE2	350	4.36	1.274	0.224	0.188	-0.224	4.189	0
PE3	350	4.61	1.308	0.175	0.154	-0.175	3.278	0
EE1	350	4.43	1.33	0.197	0.18	-0.197	3.692	0
EE2	350	4.23	1.304	0.212	0.212	-0.186	3.958	0
EE3	350	3.98	1.504	0.164	0.164	-0.153	3.069	0
SA1	350	3.9	1.412	0.255	0.22	-0.255	4.766	0
SA2	350	4.02	1.304	0.262	0.233	-0.262	4.894	0
SA3	350	3.93	1.346	0.24	0.237	-0.24	4.496	0

Legend: K-S: Kolmogorov-Smirnov Statistic

Table 3: Respondent Profile

Category	Values	Frequency	Percent
Age	18-24	64	18.2
	25-34	88	25.1
	35-44	75	21.4
	45-54	43	12.2
	55-64	32	9.1
	65-74	33	9.4
	Above 75	15	4.2
	Total	**350**	**100**
Gender	Male	173	49.4
	Female	177	50.5
	Total	**350**	**100**
Education	Diploma	45	12.8
	Graduate	162	46.2
	Postgraduate – Taught	76	21.7
	Postgraduate – Research	35	10
	Other	32	9.1
	Total	**350**	**100**
Annual Income	£10,000 - £25,000	55	15.7
	£26,000 - £50,000	67	19.1
	£50,000 - £100,000	179	51.1
	> £100,000	49	14
	Total	**350**	**100**

Table 4: Descriptive Statistics

Items	N	Mean	Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic
BI1	350	4.24	1.359	1.846
BI2	350	4.42	1.353	1.831
BI3	350	4.52	1.405	1.975
Average BI	**350**	**4.39**	**1.372**	**1.884**
PU1	350	4.25	1.296	1.680
PU2	350	4.36	1.274	1.623
PU3	350	4.61	1.308	1.712
Average PU	**350**	**4.40**	**1.292**	**1.671**
PEOU1	350	4.43	1.330	1.770
PEOU2	350	4.23	1.304	1.700
PEOU3	350	3.98	1.504	2.263
Average PEOU	**350**	**4.21**	**1.379**	**1.911**
SA1	350	3.90	1.412	1.995
SA2	350	4.02	1.304	1.701
SA3	350	3.93	1.346	1.812
Average SA	**350**	**3.95**	**1.354**	**1.836**

Legend: BI – Behavioral Intention; PU – Perceived Usefulness; PEOU – Perceived Ease of Use; SA – Social Approval

Table 5: Reliability Test

Constructs	Sample	Items	Cronbach's α	Reliability
Perceived Usefulness	350	3	.871	High
Perceived Ease of Use	350	3	.841	High
Social Approval	350	3	.880	High
Behavioural Intention	350	3	.826	High

Table 6: AVE and CR values

Latent Variables	CR Values	BI	PEOU	PU	SA
Behavioral Intention (BI)	0.926	**0.723**			
Perceived Ease of Use (PEOU)	0.762	0.428	**0.589**		
Perceived Usefulness (PU)	0.739	0.261	0.521	**0.534**	
Social Approval (SA)	0.714	0.221	0.429	0.332	**0.521**

Legend: CR – Composite Reliability; Values in **bold** – AVE Values; Others – Squared Correlations

Table 7: Principal Component Analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.812	48.437	48.437	5.812	48.437	48.437
2	2.085	17.372	65.809			
3	.855	7.125	72.933			
4	.642	5.348	78.282			
5	.565	4.707	82.988			
6	.424	3.536	86.525			
7	.352	2.937	89.462			
8	.292	2.429	91.892			
9	.281	2.344	94.236			
10	.245	2.046	96.281			
11	.228	1.899	98.181			
12	.218	1.819	100.000			
Extraction Method: Principal Component Analysis.						

Table 8: Statistical estimates for the Structural Model

Independent and Dependent Variable Relationships		Estimates		
Independent Variables	Dependent Variables	β	C.R.	P
Perceived Usefulness	Behavioral Intention	0.68	3.705	0.002
Perceived Ease of Use	Behavioral Intention	0.18	2.293	0.000
Social Approval	Behavioral Intention	0.29	2.733	0.008
Perceived Ease of Use	Perceived Usefulness	0.36	3.423	0.000
R-Square for Perceived Usefulness		0.49		
R-Square for Behavioral Intention		0.58		
Chi-Square (χ^2)		845.404		
Probability Level		0.000		
Degrees of Freedom		54		
CMIN/df (χ^2/df)		2.459		
Comparative Fit Index, CFI		0.953		
Goodness of Fit, GFI		0.940		
Adjusted Goodness of Fit, AGFI		0.803		
Normed Fit Index, NFI		0.987		
Root Mean Square Error of Approximation, RMSEA		0.058		
Sample Size		350		

Table 9: Frequencies for Perceived Usefulness

Perceived Usefulness	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
PU1	13	22	27	159	78	32	19
PU2	10	21	27	144	89	42	17
PU3	8	18	25	106	113	55	25

Table 10: Frequencies for Perceived Ease of Use

Perceived Ease of Use	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
PEOU1	11	17	34	132	83	52	21
PEOU2	6	26	54	139	67	38	20
PEOU3	18	43	62	111	55	42	19

Table 11: Frequencies for Social Approval

Social Approval	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
SA1	20	49	27	166	40	35	13
SA2	15	34	32	173	51	33	12
SA3	14	42	42	167	44	23	18

Table 12: Frequencies for Behavioural Intention

Behavioural Intention	*Extremely Disagree*	*Disagree*	*Slightly Disagree*	*Neutral*	*Slightly Agree*	*Agree*	*Extremely Agree*
BI1	18	19	28	159	65	43	18
BI2	10	18	48	107	96	49	22
BI3	12	13	46	106	83	63	27