Predictors for the Adoption of Open Data Technologies: Drawing Upon the Unified Model of Electronic Government Adoption

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Abstract: Open Data initiative is attracting considerable interest globally due to growing phenomena of transparency, accountability, quality of life, and business. Adoption of open data technologies is inevitably an issue to better exploit full potential and benefits of open data available to the public. The main issue in our knowledge of open data technologies is the scarcity of research studies on adoption of open data technologies. Thus, the foremost aim of this study is to predict and explain the predictors that influence adoption of open data technologies. The UMEGA theory was employed as a lens to examine the influencing factors including additional factors i.e. imitating behaviour of others, disregarding own beliefs, and grievance redressal. A survey questionnaire was used to collect the data from citizens and analyzed using PLS-SEM technique. Satisfactory results are obtained proving that facilitating conditions has significant positive influence on effort expectancy, effort expectancy on performance expectancy, performance expectancy on attitude, and attitude on behavioural intention to adopt open data technologies even though the number of participants are very small. Future researchers should find more concrete evidences upon collecting large number of responses.

Keywords: Open Data Technology, Predictors, Adoption, Behavioural Intention, Electronic Government, Unified Model of Electronic Government Adoption

1 Introduction

Open data has become a stimulus for public sector organization to publish their factual, objective and nonperson-specific data that is freely accessible to all and usable without any copyright restrictions (Bertot, Gorham, Jaeger, A Sarin, & A Choi, 2014; Hossain, Dwivedi, & Rana, 2015). Scholars outline that open data refers to an activity undertaken by the organizations or public to visualize, understand, analyze and use the data provided to the public by the public sector agencies (Zuiderwijk, Janssen, & Dwivedi, 2015). The footstep was first taken in the Europe in Public Sector Information directive in 2003 (Attard, Orlandi, Scerri, & Auer, 2015). The open data movement gained significant momentum after the U.S. President Barack Obama’s open data
initiative in 2009. Later, Australian Open Government Declaration in 2010 (Chatfield & Reddick, 2016), the Open Government Partnership (presently 75 countries are part of it) in 2011, and G8 Open Data Charter in 2013 (Attard et al., 2015) came into existence. However, it was technologically recognized and proposed by Sir Tim Berners-Lee (Hossain et al., 2015). In this connection, Open data portals or technologies are being introduced to provide means for free access to public sector data by all primary and secondary stakeholders.

Currently, governments of developed and developing countries are mandating the public agencies to share data with the public to reuse or distribute without any copyright obligations in order to increase transparency and accountability. Now, Open data has not been exclusive to the open government only, it has also captured the Science, Libraries, Ecosystems, and Economics disciplines as well. Moreover, national, regional, and municipal organizations are also joining the open government data movement. However, opening of some raw data or datasets (integrated set of related data) in machine-readable form on the internet for public use is not sufficient, it is also quite necessary to provide datasets those can be functionally integrated and enhanced to extract values. Open data initiative improves the delivery of public services through effective and efficient data management. This also provides an improved open data infrastructure within government to allow data to be readily accessed, used, re-sued and re-distributed without any restrictions or legal obligations by relevant stakeholders and be integrated with other datasets.

In recent years, data are becoming available by the public entities to the public openly in machine-readable formats to meet the demands for primary and secondary stakeholders whereas these stakeholders can use, reuse and distribute it without any restrictions of copyright or any other legal obligation (Gonzalez-Zapata & Heeks, 2015). However, availability of data by public entities and usage by public is enabled by open data technologies. Therefore, open data technologies enable value creation by both the primary and secondary stakeholders (Gonzalez-Zapata & Heeks, 2015). Value in the context of data enabled by open data technologies for secondary stakeholders such as citizens implies that it enables improving quality of life of the citizens, better understanding of government actions that directly affect the citizens, improved decision-making in their daily-life activities, and innovation and development by analyzing data through its extraction and transformation (Máchová, Hub, & Lnenicka, 2018; Susha, Grönlund, & Janssen, 2015). For instance, citizens may use open data technologies education-related open government data for viewing schools in her surroundings and understanding government policies for developing educational policies country-wide (PDP, 2018), scientists may use open data technologies to obtain rainfall data for the purpose of making modeling, simulations, visualizations and improved methods for accurate predictions of disasters (Younis, Majid, & Ammar, 2017), developers can develop interactive web and desktop applications (Susha et al., 2015), data analysts can make better business decisions by integrating government data with business data, tourists can explore new regions for expedition, students can perform policy research and write academic publications (Zuiderwijk et al., 2015), named a few.

Policymakers want citizens to adopt open data technologies widely, therefore, they need to understand what drives citizens to adopt open data technologies widely (Weerakkody, Irani, Kapoor, Sivarajah, & Dwivedi, 2017). A study on investigating the factors or predictors of open data technologies adoption helps policymakers to exploit value of this innovation. Moreover, understanding the factors influencing adoption of open data technologies will support public entities to make more informed future investment decisions, such as investments in terms of employing specialized staff to open the data, in terms of building infrastructure, hardware and software, time for policy and legislation, reducing the cost of travelling, offering more open data technologies, reducing the development cost of open data technologies (Kassen, 2018; Khurshid,
Zakaria, Rashid, Kazmi, & Shafique, 2019; Máchová et al., 2018), and so on. Therefore, this research attempts to fill the gap in knowledge and practice by examining the factors that influence citizens’ adoption of open data technologies by employing the UMEGA theory (Dwivedi et al., 2017).

2 Proposed Research Model for Adoption of Open Data Technologies and Hypothesis Development

The open data within public sector is considered under the umbrella, a subset, a sub-domain or an extension of e-government (Attard et al., 2015). Open data technologies are mostly offered by the public sector institutions (Hossain, Dwivedi, & Rana, 2016) to enhance transparency, to release social and commercial value, and to provide opportunities to the public in government’s decision- and policy-making (Attard et al., 2015). These technologies are to be used by different stakeholders including citizens. In this context, a Unified Model of Electronic Government Adoption (UMEGA) is employed as a lens to examine the influencing factors of adoption of open data technologies by the citizens. The UMEGA model is a recent model of electronic-government adoption. The distinction between the UMEGA model and other adoption models such as the TAM theory (Davis, 1989), and the UTAUT theory (Venkatesh, Morris, Davis, & Davis, 2003) is that it is designed, developed and validated purely for e-government (Kirat Rai, Ramamritham, & Jana, 2020; Verkijika & De Wet, 2018). The UMEGA model provides a comprehensive evaluation of previously nine well-known theoretical models, combined the constructs together and then rigorously validated it by combining outperformed variables. In presenting the unified model for the e-government adoption, it includes attitude as a protuberant component of e-government adoption (Nguyen, Dang, Van Nguyen, & Nguyen, 2020) as well as facilitating conditions as an antecedent of effort expectancy. Another reason is that the UMEGA model performed better than other technology acceptance and adoption models in the e-government context (Mensah, Zeng, & Luo, 2020).

**Figure 1: The UMEGA Model (Dwivedi et al., 2017)**

**Performance Expectancy (PE):** A similar construct has been used in developing the UTAUT theory (Venkatesh et al., 2003) as well as its extended version, that is, the UTAUT2 theory
(Venkatesh, Thong, & Xu, 2012) to study consumer’s adoption of a technology. This construct has appeared as a critical predictor in understanding system’s usefulness in earlier studies (Talukder, Shen, Hossain Talukder, & Bao, 2019). Further, a positive and significant influence of performance expectancy on behavioural intention to use digital payments adoption has also been observed in earlier studies (Rahman, Shafique, Khurshid, Asghar, & Ghafoor, 2020). The individuals’ attitudes are shaped when they expect open data technologies to be beneficial in achieving more values. In this study, performance expectancy is considered to form the citizens’ attitudes. Hence, the formulated hypothesis is outlined as follows:

H1: PE has a positive influence on attitude (ATT) toward using open data technologies.

Effort Expectancy (EE): The users’ perceptions about a technology vary and contingent upon its associated simplicity. A large number of users will be using open data technologies more when they evaluate them simple or easy to use in terms of finding, visualizing, accessing, and processing datasets. The easier the open data technologies are to understand the faster they are accepted and used by the individuals (Weerakkody, Kapoor, Balta, Irani, & Dwivedi, 2017). There are evidences found that the huge efforts restrict the individuals to adopt e-government (Verkijika & De Wet, 2018). However, the associated simplicity with open data technologies is positively linked with their adoption (Saxena & Janssen, 2017). Moreover, effort expectancy is corroborated in earlier studies with respect to e-government adoption (Dwivedi et al., 2017; Mensah et al., 2020). Following the previous evidences, following hypotheses have been proposed.

H2: EE has a positive influence on ATT toward using open data technologies.

H3: EE has a positive influence on PE toward using open data technologies.

Social Influence (SI): This construct measures the individuals’ perceptions about the influence of other individuals on adoption of technologies. It is possible that the social conditions also contribute in shaping individuals’ attitudes to adopt a technology besides technical condition such as PE and EE factors. The influence of peers, friends, or family members determine a user’s perception to use a technology. The social factor construct the individual behavioural patterns and treated as a strong predictor of public sector big open data (Weerakkody, Kapoor, et al., 2017). In earlier studies, scholars are largely hypothesizing and corroborating the influence of social conditions on technologies adoption such as e-government adoption (Avazov & Seohyun Lee, 2020; Mensah et al., 2020; Verkijika & De Wet, 2018), adoption of transactional services in e-government (Khurshid, Zakaria, Rashid, Ahmed, & Shafique, 2019) as well as adoption of open data technologies (Khurshid, Zakaria, Rashid, & Shafique, 2018; Saxena & Janssen, 2017; Zuiderwijk et al., 2015). Based on the facts, the proposed hypothesis is outlined as follows:

H4: SI has a positive influence on ATT toward using open data technologies.

Facilitating Conditions (FC): The available resources such as Internet, computer systems, networks, and public outlets are the prerequisites for using government services. The individual’s ability to use the open data technologies is affected by the provision and availability of relevant resources. Further, the knowledge and expertise also induce the individuals to use technologies because these are also the fundamental elements. Thus, skills and expertise, ICT infrastructure, appropriate datasets, and education are vital constituents of open data technologies (Saxena & Janssen, 2017; Zuiderwijk et al., 2015). The absence of such facilities severely affects as well as make the technology adoption tough.

H5: FC has a positive influence on BI toward using open data technologies.
**H6:** FC has a positive influence on EE toward using open data technologies.

**Perceived Risks (PR):** Due to the expected concerns, individuals may not be willing to adopt open data technologies. In the context of e-government, risks are considered as concerns by which an individual may suffer in some sort of losses or uncertain situations while adopting it (Verkijika & De Wet, 2018). For instance, they might expect that there are payment of fee in accessing the datasets and cost might be escalated unexpectedly as more and more datasets are accessed (Janssen, Charalabidis, & Zuiderwijk, 2012). They might have threat of lawsuits in utilizing datasets and participating in open data initiatives. The individuals might also have Internet-related risks like disclosure of their identities on the web and, therefore, limit themselves in using web technologies (Verkijika & De Wet, 2018). The poor information quality may also lead to user’s anxiety in taking decision to adopt open data technologies (Weerakkody, Irani, et al., 2017). It can be inferred that the less the risks the more the open data technologies will be adopted. There are evidences found in previous literature where risk perceptions construct is indicated as a significant factor that effect in shaping individuals’ attitudes (Dwivedi et al., 2017; Mensah et al., 2020; Verkijika & De Wet, 2018). Therefore, the following hypothesis has been formulated based on the previous evidences in the literature:

**H7:** PR has a negative influence on ATT toward using open data technologies.

**Governmental Support (GS):** Government support is described as “the initiatives of government in creating and enabling environment for the adoption of ICTs in the everyday lives of citizens”. Governments is one of the largest stakeholders that can support for using open data technologies. Since governments are providing the public data through web so as to make arrangements and facilities such as ICT hubs, service centers, computer labs, or internet cafes to utilize technologies for accessing the data. Governments also make arrangements to hold workshops to create awareness and train public regarding utilization of open data technologies. In a study conducted by Wang and Lo (2019), scholars found that government support is a crucial predictor of using open government data. However, in this study, government support is considered to have its influence on shaping citizens’ attitude and this constructing their intention to use open data technologies. Thus, the following hypothesis is formulated:

**H8:** GS has a positive influence on BI toward using open data technologies.

**Imitating Others (IMO):** A technology will be adopted by a unit of adoption when it is evident that someone is using it observing the benefits (Vinnik, 2017). Similarly, the benefits are also become evident to others while it has been using for some time. Skeptical users learn from other’s observations and deduce results regarding adoption value (Sun, 2013). It is also possible that users are not able to collect information properly about technology benefits and imitate other’s behaviour in adopting it (Vinnik, 2017). There are found evidences in earlier studies in which similar factor has been found to have a positive influence on user’s behavioural intention (Sun, 2013; Vinnik, 2017) as well as users’ attitudes (Khurshid, Zakaria, Rashid, Ahmed, et al., 2019; Khurshid, Zakaria, Rashid, Shafique, et al., 2019). Based on the facts, in this study, the below hypothesis is formulated:

**H9:** IMO has a positive influence on BI toward using open data technologies.

**Disregarding Own Beliefs (DOB):** Discounting or disregarding self-opinion about technology adoption is based on one’s self-observation of other’s behaviour on technology adoption. Disregarding own belief is not a self-instructed belief of users rather it is based on self-observation (Vinnik, 2017). People follow others and discount their own beliefs when a technology is adopted
by a large number of users. They prefer others and choose the technology to utilize it. Thus, they
discount their own preferences in adopting a technology. In earlier literature, scholars have
observed its moderating effect on changing users’ beliefs (Sun, 2013). A similar construct, that is
herd behaviour, has been found significant to have its influence on forming user’s attitudes in
intention to use transactional services (Khurshid, Zakaria, Rashid, Ahmed, et al., 2019). Another
study has also framed this factor in measuring citizen’s adoption of OIoTD (Open Internet of
Things Data) platform offered by the public sector (Khurshid, Zakaria, Rashid, Shafique, et al.,
2019). Therefore, accordingly, the following hypothesis has been formulated:

**H10:** DOB has a positive influence on BI toward using open data technologies.

**Attitude (ATT):** The level of positive appraisals or evaluations affect the individuals’ intention to
use services and technologies. There are plenty of evidences in earlier literature which validate the
association between attitude and intention in the e-government context (Khurshid, Zakaria, Rashid,
Ahmed, et al., 2019; Kirat Rai et al., 2020; Verkijika & De Wet, 2018). Accordingly, it is
hypothesized that the high intention to use open data technologies is influenced by the individual’s
positive evaluations or appraisals.

**H11:** ATT has a positive influence on BI toward using open data technologies.

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![The Research Model – Extended UMEGA](image)

*Figure 2: The Research Model – Extended UMEGA*

The influence of performance expectancy, effort expectancy, social influence, and perceived risks
are examined on citizens’ attitude whereas facilitating conditions is hypothesized as the predictor
of both effort expectancy and behavioural intention. Effort expectancy is also hypothesized to have
an influence on performance expectancy. Further, government support, imitating others,
disregarding own beliefs, and attitude are hypothesized to have their influence on behavioural intention. A complete model is depicted in Figure 2.

3 Methods

Pakistan is a developing country which is at initial stage with respect to open data technologies. Pakistan was selected in order to test and validate the UMEGA theory and its extended version. This administrative region was selected because researchers found it easy to collect suitable data. Another reason is its participation in Open Government Partnership initiative. However, the uptake of open data technologies is very slow in Pakistan.

A quantitative study was adopted to test the UMEGA theory and to empirically investigate the formulated hypotheses. A survey questionnaire approach was used to collect the data. All the constructs and their items in the questionnaire were adopted from previous studies and provided in Appendix A. These studies included (Dwivedi et al., 2017; Kumar, Adlakaha, & Mukherjee, 2018; Saxena & Janssen, 2017; Sun, 2013; Talukder et al., 2019; Vinnik, 2017; Zuiderwijk et al., 2015). Data was collected from the citizens in Pakistan through the online developed survey. The data collection process was not outsourced rather the data were collected through self-administered online questionnaire only. A total of 54 citizens provided their feedback using online survey and the data collection task was carried out during the month of September 2019. Respondents were asked to mark their level of agreement against each question based on seven-point scales ranged from “Extremely Disagree” to “Extremely Agree”. A small introduction about open government data was presented before the respondents to give them an understanding about open data technologies. The UMEGA theory was extended to determine the factors which influence the adoption of open data technologies (Dwivedi et al., 2017).

The sampling technique that was adopted in this research was random. Since, 100% of respondents of this survey were well-educated, this suggested a high degree of competency to answer the questionnaire. Therefore, this provided us confidence in evaluating the suitability of respondents for this study.

4 Findings

4.1 Demographics

Of the study population, 77.8% are males and 22.2% are females. A major chunk of respondents (55.5%) are 30-39 years old, followed by 22.2% of age bracket between 40-49 year. Moreover, qualification level of all the participants is at least ‘Graduate’. Awareness of citizens about open data technologies are also observed. It is found that 22.2% citizens are aware of Pakistan Data Portal and Disaster Info each, 37% of Punjab Open Data Portal, 11.1% of Pakistan's Economic and Social Data Resources, and Open Data Initiative-Government of Punjab, whereas 44.4% citizens do not aware of any open data technologies.

4.2 Measurement Model

PLS-SEM comprised of two parts i.e. Measurement Model and Structural Model. Measurement Model with reflective constructs is determined by performing reliability and validity tests. For reliability checking, Cronbach’s Alpha and composite reliability tests are carried out whereas Content, Convergent, and Discriminant validity test are carried to check validity. Values of Cronbach’s Alpha, composite reliability, content validity, and convergent validity must be greater than 0.6 whereas AVE must be greater than 0.5 for evaluation of structural model (Hair, Hult, Ringle, & Sarstedt, 2017; Nunnally & Bernstein, 1994). Since all the values are greater than the
minimum acceptable value, structural model has been evaluated to test the hypotheses (see Table 1 and Table 2).

**Table 1: Cronbach's Alpha, Composite Reliability and AVE statistics**

| Constructs                  | Item Code | Factor Loadings | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|-----------------------------|-----------|-----------------|------------------|-----------------------|----------------------------------|
| Attitude                    | AT1       | 0.844           | 0.882            | 0.927                 | 0.809                            |
|                             | AT2       | 0.898           |                  |                       |                                  |
|                             | AT3       | 0.953           |                  |                       |                                  |
| Behavioural Intention       | BI1       | 0.925           | 0.811            | 0.879                 | 0.649                            |
|                             | BI2       | 0.661           |                  |                       |                                  |
|                             | BI3       | 0.890           |                  |                       |                                  |
|                             | BI4       | 0.715           |                  |                       |                                  |
| Disregarding own Beliefs    | DOB1      | 0.843           | 0.691            | 0.865                 | 0.762                            |
|                             | DOB2      | 0.902           |                  |                       |                                  |
| Effort Expectancy           | EE1       | 0.861           | 0.795            | 0.873                 | 0.696                            |
|                             | EE2       | 0.824           |                  |                       |                                  |
|                             | EE4       | 0.818           |                  |                       |                                  |
| Facilitating Conditions     | FC1       | 0.843           | 0.864            | 0.916                 | 0.785                            |
|                             | FC3       | 0.941           |                  |                       |                                  |
|                             | FC5       | 0.872           |                  |                       |                                  |
| Government Support          | GS1       | 0.950           | 0.891            | 0.924                 | 0.803                            |
|                             | GS2       | 0.880           |                  |                       |                                  |
|                             | GS3       | 0.856           |                  |                       |                                  |
| Imitating Other             | IMO1      | 0.715           | 0.711            | 0.837                 | 0.634                            |
|                             | IMO2      | 0.898           |                  |                       |                                  |
|                             | IMO3      | 0.764           |                  |                       |                                  |
| Perceived Risk              | PR1       | 0.646           | 0.804            | 0.863                 | 0.683                            |
|                             | PR2       | 0.853           |                  |                       |                                  |
|                             | PR3       | 0.951           |                  |                       |                                  |
| Performance Expectancy      | PE1       | 0.887           | 0.893            | 0.933                 | 0.824                            |
|                             | PE3       | 0.940           |                  |                       |                                  |
| Social Influence            | SI1       | 0.914           | 0.653            | 0.786                 | 0.558                            |
|                             | SI2       | 0.685           |                  |                       |                                  |
|                             | SI3       | 0.609           |                  |                       |                                  |

**Table 2: Heterotrait-Monotrait Ratio (HTMT) Statistics**

|               | ATT | BI | DOB | EE  | FC  | GS  | IMO | PR  | PE  |
|---------------|-----|----|-----|-----|-----|-----|-----|-----|-----|
| BI            | 0.867 |    |    |     |     |     |     |     |     |
| DOB           | 0.296 | 0.358 |    |     |     |     |     |     |     |
| EE            | 0.554 | 0.639 | 0.258 |     |     |     |     |     |     |
| FC            | 0.683 | 0.577 | 0.310 | 0.596 |     |     |     |     |     |
| GS            | 0.092 | 0.265 | 0.272 | 0.525 | 0.127 |     |     |     |     |
| IMO           | 0.660 | 0.772 | 0.249 | 0.629 | 0.734 | 0.417 |     |     |     |
| PR            | 0.238 | 0.268 | 0.157 | 0.290 | 0.204 | 0.212 | 0.465 |     |     |
| PE            | 0.782 | 0.794 | 0.423 | 0.712 | 0.534 | 0.221 | 0.611 | 0.242 |
4.3 Structural Model

In structural model, explanatory factors ($R^2$) and significant values ($p$ values) are the most crucial values to assess the structural model. The values of $R^2 0.02, 0.13$ and $0.26$ are categorized as low, medium and high explanatory variance (Hair et al., 2017). The $R^2$ value of effort expectancy is $0.321$, performance expectancy is $0.393$, attitude is $0.553$, and $R^2$ value of behavioural intention is $0.638$ (see Figure 3). It is found that there is high explanatory variance, since the $R^2$ value of all these constructs are greater than $0.26$. The $p$ values less than $0.05$ show the significant values and acceptance of hypothesis.

Table 3: Path Analysis and Remarks on Hypothesis

| Paths       | Path Coefficient | Standard Deviation | t-Statistics | p Values | Remarks   |
|-------------|------------------|--------------------|--------------|----------|-----------|
| ATT -> BI   | 0.607            | 0.208              | 2.910        | 0.004    | Accepted  |
| DOB -> BI   | 0.080            | 0.176              | 0.451        | 0.652    | Not Accepted |
| EE -> ATT   | 0.183            | 0.138              | 1.324        | 0.186    | Not Accepted |
| EE -> PE    | 0.627            | 0.168              | 3.733        | 0.000    | Accepted  |
| FC -> BI    | -0.007           | 0.402              | 0.017        | 0.987    | Not Accepted |
| FC -> EE    | 0.567            | 0.150              | 3.785        | 0.000    | Accepted  |
| GS -> BI    | 0.175            | 0.227              | 0.770        | 0.441    | Not Accepted |
| IMO -> BI   | 0.201            | 0.311              | 0.646        | 0.518    | Not Accepted |
| PR -> ATT   | -0.227           | 0.212              | 1.069        | 0.285    | Not Accepted |
| PE -> ATT   | 0.568            | 0.159              | 3.579        | 0.000    | Accepted  |
| SI -> ATT   | 0.039            | 0.233              | 0.166        | 0.868    | Not Accepted |

Performance Expectancy
R Square=0.393

Effort Expectancy
R Square=0.321

Social Influence

Facilitating Conditions

Perceived Risks

Government Support

Imitating Others

Disregarding own beliefs

Significant

Nonsignificant

Behavioural Intention
R Square=0.638
5 Discussion

This study has given an account of predicting citizens’ adoption of open data technologies. The results have strengthened our confidence in hypothesis that PE is the most significant predictor of ATT followed by FC on EE and followed by ATT of the behavioural intention to use open data technologies (Saxena & Janssen, 2017; Talukder et al., 2019; Zuiderwijk & Cligge, 2016; Zuiderwijk et al., 2015). Being H1 to be positive and significant indicates that citizens would be forming positive ideas about open data technologies if these technologies enable them to complete their tasks quickly and find useful in their daily lives which, in turn, have an influence in building citizens’ attitudes. Being H3 to be positive and significant reveals that the more the citizens feel simple and easy to adopt open data technologies, the more useful they find these technologies in their daily lives. Being H6 to be positive and significant shows that it would be simple for citizens to adopt open data technologies if they find necessary resources, knowledge, and infrastructure. Moreover, being H11 to be positive and significant means that citizens’ positive and negative evaluations about open data technologies would form their willingness, plan, and likelihood of using them (Saxena & Janssen, 2017; Talukder et al., 2019; Zuiderwijk & Cligge, 2016; Zuiderwijk et al., 2015).

The results are distinguishable from UMEGA (Dwivedi et al., 2017) where PE, EE, SI, and PR are found to be the significant predictors of ATT whereas FC is the significant predictor of both EE and behavioural intention. Therefore, the results are not in good agreement with UMEGA (Dwivedi et al., 2017) at this stage where there are low number of participants. Apart from these disagreements, the results are expected to confirmation of UMEGA Model on large number of respondents. These results, thus, need to be interpreted with caution of limited number of participants.

Our study has been unsuccessful in proving that DOB, FC, GS, IMO, and PR have significant impacts on behavioural intention to use open data technologies. It is also unsuccessful in proving that EE and SI have significant impacts on ATT. In this context, there is, certainly, a large room for improvements in studying the influencing factors on adoption of open data technologies by increasing the number of responses. Therefore, discrepancies in results may be negligible since the sample size is very small in measuring the determinants of adoption of open data technologies.

6 Conclusion

To sum up, this work has investigated the predictors of adoption of open data technologies by employing the UMEGA theory since open data technologies come under electronic-government services to provide government data to the public. Data on the constructs and their relevant items was collected through survey from citizens of Pakistan. The developed model explains 32% variance in EE, 39% in PE, 55% in ATT, and 63% of the variance in behavioural intention to adoption open data technologies. The obtained results are satisfactory proving that FC has significant positive influence on EE, EE on PE, PE on ATT, and ATT on behavioural intention to use open data technologies even though the number of participants are very small. This study provides virtuous foundations to provide evidence about predicting the adoption of open data technologies using a new theoretical model i.e. the UMEGA (Dwivedi et al., 2017) and by extending it. Findings of this study add understanding of open data technologies adoption factors and little implications for the government, practitioners, and managers. This study is going on collecting data from citizens on the factors influencing adoption of open data technologies and will provide concrete evidences upon collecting large number of responses. This study should be
extended by the future scholars by conducting a comparison study among adoption factors of different open data technologies.

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Appendix A

**Constructs and Items**

**Performance Expectancy**
Performance Expectancy is defined as “the degree to which a person believes that using the system will assist him or her in accomplishing improvements in job performance”.
PE1: Using open data technologies would enable me to accomplish tasks quicker.
PE2: Using open data technologies would enhance my effectiveness.
PE3: Using open data technologies would make it easier to get my tasks done.
PE4: I would find open data technologies useful in my daily life.

**Effort Expectancy**
Effort expectancy is defined as “the level of simplicity associated with the use of a system”.
EE1: I would find it easy to get the open data technologies to do what I want it to do.
EE2: Learning to use open data technologies will be easy for me.
EE3: I would find open data technologies easy to use.
EE4: My interaction with open data technologies would be clear and understandable.

**Social Influence**
Social influence is defined as “the degree to which a person perceives that important others believe that he or she should use a new system”.
SI1: People who influence my behaviour think that I should use open data technologies.
SI2: People who are important to me think that I should use open data technologies.
SI3: I would use open data technologies because of the type of people who use the system.
SI4: In general, the Institution would support the use of open data technologies.

**Facilitating Conditions**
Facilitating conditions are defined as the level to which a person believes that an organizational and technical infrastructure is available to support the use of a system.
FC1: I would have command over using open data technologies.
FC2: I would have the knowledge necessary to use open data technologies.
FC3: Given the resources, opportunities and knowledge, it would be easy for me to use open data technologies.
FC4: The open data technologies would be compatible with the other systems I use.
FC5: Specialized instruction concerning open data technologies would be available to me.

**Perceived Risks**
Perceived risk is defined as “the conviction that he or she will suffer a loss while seeking an outcome”.
PR1: Use of open data technologies may cause my personal information to be stolen.
PR2: I would feel uneasy psychologically if I use open data technologies.
PR3: I think that it is unsafe to use open data technologies because of the privacy and security concerns.
PR4: I believe that there could be negative consequences by using open data technologies.

**Governmental Support**
Government support is described as “the initiatives of government in creating and enabling environment for the adoption of ICTs in the everyday lives of citizens”.
GS1: The government would be providing adequate facilities (e.g. ICT hubs, service centers, labs, or internet cafes) to use open data technologies.
GS2: The government would be fulfilling its responsibilities of creating awareness and education to people about the existence of open data technologies.
GS3: The government would be giving training to the citizens to make the best use of open data
technologies.

**Imitating Others**
Imitating behaviour of others is described as “the degree to which a person will follow other’s decisions when adopting a technology”.
IMO1: If open data technologies seem to be a dominant system, I would like to use it.
IMO2: I would follow others in accepting and using open data technologies.
IMO3: I would choose to accept and use open data technologies if other people would be using it.

**Disregarding own Beliefs**
Disregarding own beliefs is described as “the degree to which a person disregards his/her own beliefs about a particular technology when making an adoption decision”.
DOB1: My acceptance and use of open data technologies would not reflect my own preferences of using it.
DOB2: I would not make the decision based on my research and information when choosing open data technologies.
DOB3: If I would not know that a lot of people have already been using open data technologies, I would not use it.

**Attitude**
Attitude toward behaviour is defined as “the level to which an individual has a positive or negative evaluation or appraisal of the behaviour in question”.
AT1: Using open data technologies would be a good idea.
AT2: Using open data technologies would be a wise idea.
AT3: I like the idea of using open data technologies.

**Behavioural Intention**
Behavioral intention is defined as “the likelihood of an individual being involved in certain behavior”.
BI1: I intend to use open data technologies in the future.
BI2: I predict that I will use open data technologies.
BI3: I am willing to use open data technologies in the future.
BI4: I plan to use open data technologies in the future.

**Demographics**
Gender
Female
Male

Age
18–24 years.
25-29 years.
30-34 years.
35-39 years.
40-44 years.
45-49 years.
50-54 years.
55-59 years.
Above 59 years.

Education
Non-Matriculation (Primary Education).
Matriculation (Secondary Education/SSC).
Intermediate (Higher Secondary Education/HSC).
Graduate (BA, B.Com, BSc, BBA, Btech, MBBS, LLB etc..)
Postgraduate (MA, Mcom, MSc, MBA, Mtech, MD, LLM etc.).
Postgraduate Research (Mphil, DBA, PhD etc.).
Other.

Awareness Level
1. Pakistan Data Portal (http://www.data.org.pk/).
2. Punjab Open Data Portal (http://open.punjab.gov.pk/).
3. Disaster Info (https://mangomap.com/national-disaster-management-authority-pakistan/maps).
4. Pakistan's Economic and Social Data Resources (http://dru.lums.edu.pk/dslist.php).
5. Open Data Initiative, Government of Punjab (http://odi.itu.edu.pk/).
6. Do not know.
7. Others.