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Do personality traits influence the user's behavioral intention to adopt and use Open Government Data (OGD)? An empirical investigation

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A R T I C L E I N F O

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A B S T R A C T

The academic interest in the Open Government Data (OGD) domain has been burgeoning over the years. Conceding that the prime focus of an OGD initiative is its further re-use for value creation and innovation by stakeholders, the present study seeks to underscore the role of HEXACO personality traits on behavioral intention (BI) to adopt and use OGD in developing countries' context. We investigate the direct, indirect, and moderating effects of HEXACO personality traits provide a better understanding of how and to what extent personality traits influence future behavioral intention to use OGD. The results demonstrate that Trust and Performance Expectancy are positive predictors of BI to adopt and use OGD. Users with higher Openness to Experience tend to have higher Effort and Performance Expectancy; are characterized by exposure to Social Influence; have higher level of Trust and positive experience of Facilitating Conditions and Information Quality. Agreeable people are more likely to Voluntarily Use OGD. Conscientiousness enhances the individual's perception of OGD quality-related factors. Excessive Emotionality affects negative perception to System and Information Quality issues. Honesty–Humility and Extraversion are able to maintain the effect of OGD Information Quality and Trust on users' BI. Our findings could be useful for practitioners to level the divergence between actual and potential use of OGD by considering the user's personality traits.

1. Introduction

As Information and Communication Technology (ICT) is coming of age, rapid strides are being made in diverse domains inclusive of the public sector. Such instances of convergence propelled the attention of the academicians and practitioners to foray into unraveling the intricacies entailed therein conceding that the dynamic landscape of public management with an emphasis on the "smartness" of the public sector envisions the resolution of societal problems through co-creation, co-production and collaboration with the citizens

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themselves (Criado et al., 2021). One such instance relates to the interface of the government and citizens via the Open Government phenomenon which is a culmination of the electronic governments (e-governments) in a bid to promote transparency, trust and accountability apart from realizing the overarching goals of the economy, efficiency and effectiveness in public service delivery formats (Zhenbin et al., 2020). A significant offshoot of Open Government relates to the provision of the public data, that was hitherto reserved in silos, via government websites in user-friendly formats (XLS, CSV, for instance) for value creation and innovation by a multitudinous set of stakeholders (citizens, academia, non-profit sector, businesses and the like). This data that is freely available for re-use is referred to as Open Government Data (OGD), Open Public Data (OPD) or Public Sector Information (PSI). For the present purpose, we will stick to the OGD nomenclature to avoid ambiguity.

Research veering around “technology usage” is associated with the technological, social and psychological reasons for the usage and adoption of a particular technology. OGD also fits well in the “technology” rubric given the fact that the datasets are being made accessible online and ipso facto, the technological edifice needs to be in place for the realization of the goals of the OGD initiatives. Significant research is available on the OGD usage behaviour by deploying the technology usage and acceptance models (TAM, UTAUT, etc.) (Purwanto et al., 2020a; Saxena and Janssen, 2017; Talukdar et al., 2019; Zuiderwijk et al., 2015). However, as already noted in a number of studies, there is increasing evidence that differences in personality traits affect the acceptance and use of IT. Hitherto, limited-yet-valuable research is available to deepen our understanding of how personality traits impact technology usage and adoption by individuals (Parasuraman, 2000; Lam et al., 2008) and invocation of personality traits in research has mainly deployed the Big-5 personality traits’ inventory in many cases. However, no attempt has been made so far to understand how personality traits influence OGD adoption and usage by individuals. Moreover, such a comprehensive HEXACO-100 inventory for analyzing personality traits (Lee & Ashton, 2018) also has not yet been tested in combination with technology usage and acceptance models for exploring their joint effect on the behavioral intention to adopt and use Open Government Data (Rizun et al., 2023).

This research *aims* to bridge this gap, by providing a better understanding of how and to what extent personality traits influence future behavioral intention to use OGD among its actual or potential end users – current undergraduate and graduate students in India. Our *contribution* to the literature on OGD initiatives’ acceptance in developing countries lies in demonstrating the powerful potential of personality traits in building and altering patterns of OGD users’ behavioral intentions. From a *methodological* perspective, we contribute by introducing a systematic process for constructing and evaluating a model that enables an understanding of the nature of previously unexamined composite impact (direct, moderating, and indirect) of personality traits on behavioral intention to adopt and use OGD. *Implications* of this research consist in providing recommendations for practitioners to level the divergence between actual and potential use of OGD by considering the impact of personality traits on user behavior. Future *research avenues* are also proposed that will help advance our understanding of the role that personality traits play in shaping the behavioral intention to adopt and use OGD.

The paper is structured as follows: Section 2 covers the theoretical background across personality, technology adoption and usage of OGD; Section 3 leads us to the research method adopted in the study; Section 4 provides an account of the results and their analysis; the penultimate Section 5 provides an overview of the discussion and implications and the concluding section 6 provides a gist of the study.

2. Research model and hypothesis development

2.1. OGD and technology adoption and usage

As the culmination of e-government alongside the forays made in providing the “freedom to information” to all, OGD implies the provision of the hitherto-reserved public data for public use via the dedicated online portals of the government. Implicitly, OGD pertains to the data linked with the diverse sectoral domains like environment, weather, energy, finance, education, health and the like. For realizing the optimum benefits of OGD initiative, it is important that the OGD portals should be equipped with advanced tools for data discovery, data visualization and user feedback apart from ensuring that the quality of the datasets is well-maintained (i.e. datasets should be complete, provided with metadata, available in machine-processable file formats, be available on the support of RDF and SPARQL and should be amenable to linking and combining from diverse sources (Alexopoulos et al., 2018). The idea behind the OGD initiative is to promote transparency, accountability, inclusiveness, citizen trust, social control and citizen participation apart from bringing about the economy, efficiency and effectiveness in public service delivery (Janssen et al., 2017; Matheus and Janssen, 2020; Zhao & Fan, 2021; de Juana-Espinosa & Lujan-Mora, 2019). As the term indicates, OGD is a “non-excludable resource” which implies that OGD is free to access by one and all as per the open-access license framework (Jetzek et al., 2019). OGD initiatives of the government envisage the re-use of the datasets for value creation and innovation by a diverse set of stakeholders (i.e. citizens, the academic community, businesses, the non-profit sector, journalists and the like) and it has been pointed out that OGD initiatives bolster the economy of the country as well (Leviakangas & Molarius, 2020).

It merits pointing out that OGD may be conceptualized in terms of being a “technology” due to its fundamental reliance on an Information Technology (IT) platform - open data portal (Kalampokis et al., 2011; Afful-Dadzie & Afful-Dadzie, 2017a; Zuiderwijk et al., 2015) and like any other “technology”, its research treatment needs to unravel the various dimensions associated with the technology adoption and usage. In the Information Systems (IS) evaluation literature, many research models have been outlined to study individual behavior towards the adoption and usage of any technology. For instance, the Theory of Reasoned Action (TRA) model proposed by Fishbein and Ajzen (1975), the Technology Acceptance Model (TAM) given by Davis (1989), the Theory of Planned Behavior (TPB) proposed by Ajzen (1991) and the Unified Theory of Acceptance and Use of Technology (UTAUT) model given by Venkatesh and his colleagues (2003) among others may be counted as significant reference-pointers to study technology adoption and usage across diverse contexts. Every new model following the chronological order is based on its predecessors adding or re-structuring or altering variables, aspects and elements.

For the present study, we will invoke an adapted model of UTAUT wherein the constructs may be conceived as per Table 1 (adapted from Lnenicka et al., 2022). In adapted model integration was made from (1) empirically tested UTAUT models that were used previously (Zuiderwijk et al., 2015; Saxena & Janssen, 2017; Talukder et al. 2019) with (2) system quality, information quality, data quality and trust components with aim to emphasize the role of open data portals in existing OGD ecosystems and test the impact of open data portals features on user experience (Purwanto et al., 2020a; Rizun et al., 2023). This study also aligns with one of the primary research agendas in the OGD field posed by (Wirtz et al., 2022), specifically, how can IS theories and explanatory models, in particular TAM, UTAUT and the DeLone-McLean IS success model, be applied in the context of research and development of OGD theory to explain acceptance, adoption and usage behavior. Following the key tenets of adapted constructs and findings from previous OGD-related studies, we introduce nine main hypothesizes about nine constructs effect on behavioural intention for OGD use (Table 1).

2.2. OGD initiative in India: A background

As in any developing country where the OGD initiatives are undertaken to usher a transparent, participative and serviceable government in line with the anticipation of its citizens (Afful-Dadzie & Afful-Dadzie, 2017b; Purwanto et al., 2020b; Talukder et al., 2019), the Indian experiment with OGD initiative has been a momentous one as it emerges over the years. As a part of the Digital India campaign, OGD initiative (https://data.gov.in) in India is provisioned since 2012 under the aegis of the National Informatics Centre (NIC) (MEITY, 2023; Deo, S., & Basrur, A., 2023). As such, the OGD initiative adheres to the Open Data Policy, i.e. the National Data Sharing and Accessibility Policy (NDSAP) with the overarching aim of provisioning public data in machine-processable formats. The initiative rests its edifice on the “Information for All” paradigm (NIC, 2023a) with more than 3.77 lac resources and 8223 catalogs (NIC, 2023b). OGD initiatives in India as well in the States are moving forward to streamline their data management practices (ORF, 2022). Implicitly, the stakeholders hailing from diverse backgrounds including academic community – as in our study – stand to gain from OGD initiatives by reusing the openly accessible OGD. Finally, it has been estimated that with the robust OGD initiatives in places, the national as well as states’ levels shall benefit from the same in terms of providing refurbished services to the citizens (KPMG, 2023).

Table 1
Constructs of adapted UTAUT model and hypothesis developed ().

Construct	Definition	Construct reference	Hypothesis
Performance expectancy (PE)	The extent to which an individual believes that using the OGD will facilitate her or him realising benefits in job performance	Venkatesh et al. (2003), UTAUT	H1: *Performance Expectancy is positively related to Behavioral Intention to adopt and use OGD* (Saxena & Janssen, 2017; Barnett et al., 2014; Zuiderwijk et al., 2015)
Effort expectancy (EE)	The extent to which an individual perceives the easiness linked with the implementation/use of the OGD	Venkatesh et al. (2003), UTAUT	H2: *Effort Expectancy is positively related to Behavioral Intention to adopt and use OGD* (Lakhal & Khechine, 2017; Saxena, S. & Janssen, M., 2017; Zuiderwijk et al., 2015)
Social influence (SI)	The extent to which an individual comprehends the significance of others’ perceptions for him/her to use a OGD	Venkatesh et al. (2003), UTAUT	H3: *Social Influence is positively related to Behavioral Intention to adopt and use OGD* (Talukder et al., 2019; Zuiderwijk et al., 2015)
Facilitating conditions (FC)	The extent to which an individual believes that an organisational and technical infrastructure exists to support the use of OGD	Venkatesh et al. (2003), UTAUT	H4: *Facilitating Conditions are positively related to Behavioral Intention to adopt and use OGD* (Talukder et al, 2019; Nguyen, 2022; Zuiderwijk et al., 2015)
Voluntariness of use (VU)	The extent to which an individual perceives that OGD use is voluntary or of free will	Moore & Benbasat (1991)	H5: *Voluntariness of Use is positively related to Behavioral Intention to adopt and use OGD* (Talukder et al., 2019; Zuiderwijk et al., 2015)
System quality (SQ)	The extent to which the performance of the information system in terms of reliability, convenience, ease of use, functionality and other system metrics influences individual willingness to adopt OGD	DeLone & McLean (2003)	H6: *System Quality is positively related to Behavioral Intention to adopt and use OGD* (Lenenicka et al., 2022)
Information quality (IQ)	The extent to which the characteristics of the output offered by the information system, such as accuracy, timeliness and completeness influence individual willingness to adopt OGD.	DeLone & McLean (2003)	H7: *Information Quality has a positive effect on Behavioral Intention to adopt and use OGD* (Lenenicka et al., 2022)
Data quality (DQ)	The extent to which OGD are free from errors, complete, accurate, appropriately formatted as per standards and ready for reuse	Purwanto, Zuiderwijk & Janssen (2020)	H8: *Data Quality has a positive effect on Behavioral Intention to adopt and use OGD* (Lenenicka et al., 2022)
Trust (T)	The extent to which OGD can be trusted	Purwanto, Zuiderwijk & Janssen (2020)	H9: *Trust has a positive effect on Behavioral Intention to adopt and use OGD* (Purwanto, Zuiderwijk, & Janssen, 2020a; Janssen, Charalabidis, & Zuiderwijk, 2012)
Behavioral intention (BI)	The extent of readiness and willingness to use OGD	Venkatesh et al. (2003), UTAUT	–

adapted from Lnenicka et al., 2022

2.3. Personality traits and technology usage and acceptance

Personality is a broadly-conceived term which implies how an individual responds to particular situations. It covers the entire gamut of aspects like an individual's thoughts, feelings and behaviors and how these aspects differ from one individual to another. Another dimension of personality is that it remains stable over time and circumstances (Phares & Chaplin, 2009). Personality is, by and large, a factor of heredity, social surroundings, familial ties, place of birth and belongingness, natural conditions, etc. Personality traits determine how an individual perceives or responds to a given situation. Extending this line of thought a little further, it may be understood that there is a linkage between an individual's personality traits and the dispositions and attitudinal behavior of individuals towards technology usage and adoption.

A number of modular formats are in place to assess personality and concomitantly, many dimensions have been identified by psychologists. For instance, Cattell proposed a two-tiered personality structure with 16 primary factors (PFs) and 5 secondary factors (Cattell, 1973). Thereafter, Eysenck (1967) enumerated three personality traits-extraversion, neuroticism and psychoticism-to describe human personality. Goldberg (1990) gave the Big-5 model covering openness, conscientiousness, extraversion, agreeableness and neuroticism. Finally, a more comprehensive and extended version of Big-5 version was propounded by Lee and Ashton as the HEXACO-100 inventory (Lee & Ashton, 2018) which rests its edifice on the factorial structure of personality and identifies six factors of personality (Abbasi et al., 2020): *Honesty-Humility* (individual changes in propensities of being "fair, honest and humble versus manipulative, pretentious and materialistic"), *Emotionality* (individual variances in a person's tendencies to be "nervous, sentimentality, and empathy versus courage, detachment, and individuality"), *Extraversion* (being assertive, sociable, and demonstrative), Agreeableness (modesty, compliance, and straightforwardness), *Conscientiousness* (being organized, dependable, thorough, and exacting), *Openness to Experience* (flexibility in seeking new experiences) and Altruism (empathy and intention to help) (Ashton & Lee, 2007; Lee & Ashton, 2018). The instrument has 100 items in all measured on a 5-point Likert scale (1-disagree; 5-agree).

The behavioral intentions in various problem areas has been discussed in previous studies (Barnett et al., 2014; Devaraj et al., 2008; Lakhal & Khechine, 2017; Sindermann et al., 2020; Wang et al., 2012b; Zhou & Lu, 2011). In the extant literature (Appendix 1), three main directions of studying the effect of personality traits on behavioral intentions (BI) to use and adopt the technology (specifically, the UTAUT) are successfully addressed: the first (least represented) examines the *direct* effect of personality traits on BI to use the technology. The second direction (most actively represented) concerns the study of the personality traits that influence BI *indirectly* - that is, through technology adoption as a mediator. The last one is related to testing the personality traits as variables that *moderate* the technology use and adoption effect on BI.

To generalize the state-of-art studies presented in extant literature (Appendix 1), it may be deduced that the scientific interest in studying the effect of personality traits on the behavioral intention to use emerging technologies is growing rapidly. UTAUT-personality dimensions linkages have been clinched in the academic and non-academic settings involving a heterogenous set of users across different locales to solicit the latter's perspectives on the adoption and usage of different technologies. Previous research has confirmed the presence of a latent relationship between personality traits and the adoption of new technology arguing that personality traits can strengthen or weaken a person's willingness or attitude towards behavior. But no definitive conclusions have yet been made. In this regard, we can summarize, that *firstly*, it is known that context matters in technology-related research (Wang & Yang, 2005). So far, no studies have been found that have tested the effects of personality traits in the context of behavioral intention to use OGD. *Secondly*, such an extended model as HEXACO was not involved in this kind of research, which means that not all possible personality trait factors have been explored yet in terms of their impact on users' behavioral intention to adopt the technology. *Finally*, as some previous studies demonstrated (Maican et al., 2019, Wang & Yang, 2005), the behavioral intention to use and adopt technology can be influenced by a comprehensive form, that is, a combination of several types of personality traits influence – direct, indirect and moderating, which requires additional study in the context of OGD (Rizun et al., 2023). Thus, in order to fill these gaps, we first, study each type of HEXACO personality traits effect in separate models so that they would allow us to hypothesize about the possibility and nature of the combination of personality traits effects types' on behavioral intention to use and adopt OGD in the final model.

Hence, to provide a deeper understanding of how and to what extent personality traits affect the behavioral intention to use OGD in the future, this paper is guided by the following research questions (RQ): RQ1: "*How and to what extent personality traits directly affect Behavioral intention to adopt and use OGD*?"; RQ2: "*How and to what extent personality traits indirectly affect Behavioral intention to adopt and use OGD*?"; RQ3: "*How and to what extent are personality traits moderating the relationship between technology adoption factors and Behavioral Intention to adopt and use OGD*?"; RQ4: "*How and to what extent do personality traits have a combined (direct, moderating or indirect) effect on Behavioral intention to adopt and use OGD*?".

Due to the fact that, as noted above, there is no single study that tests the influence of personality traits on behavioral intention to use OGD, we will develop all our hypotheses by adapting the results of the relevant literature regarding the adoption and use of technologies to the context of OGD. The three types of hypotheses are explained in the section 2.2.1.

2.4. Hypothesis development

Honesty–Humility. Individuals scoring high on this dimension are "sincere, honest and, modest and are more likely to cooperate with others; on the contrary, people with a low level of honesty-humility are inclined to be presumptuous, dominant, and manipulative, and to break the rules to gain their own advantages" (Morelli et al., 2020:3). In (Gnisci et al., 2011) study, internet dependence was found to be significantly negatively linked with honesty-humility dimension. In another instance, honesty-humility was found to have direct positive impact of personality characteristics in both offline (Wagner et al., 2014) and online (NOE et al. 2016) social networks. Honesty-humility is also positively associated with sincere and fair interpersonal and intergroup collaboration (Hilbig et al., 2018), and decreased cheating behavior (Ścigała et al., 2019). In the context of OGD we expect that people with high honesty-humility trait are likely to show a stronger desire to adopt and use open data for more transparent and fair government-citizen interactions through Open Government:

H10A: *Honesty-Humility will be positively associated with Behavioral Intention to adopt and use OGD*.

In another instance, honesty-humility was not found to have any direct effect on predicting user video game engagement (Abbasi et al., 2020) and Facebook usage and Facebook network characteristics (Brown, Roberts & Pollet, 2018). On the other hand, according to (Sindermann et al., 2020), individuals who score lower in honesty-humility are more likely to show higher levels of TAM indicators (such as perceived usefulness, perceived ease of use) with wit regard to technological devices. Those who score high in honesty-humility are likely to be more truthful about their use of technologies. Because prior studies did not measure honesty-humility in the context of OGD and UTAUT (see section 2.2), we can only theorize that:

H10B_1-H10B_9: *Honesty-Humility will be positively associated with each of the OGD-related Nine technology adoption factors*.[1]

We expect to find positive significant moderative effect of honesty-humility on relationship between some of technology adoption factors and Behavioral Intention to use and to adopt and use OGD. Having no direct evidence of such an positive moderating effect in extant literature, we can assume its presence, since, on the one hand, it is known that Agreeableness is positively moderated the relationship between subjective norms and intention to use Collaborative System (Devaraj et al., 2008; Ramirez-Correa et al., 2019); on the other hand, agreeableness and honesty-humility demonstrate a strong positive correlation in the context of interpersonal competency, computer games adoption, pro-social and ethical behavior and (Wang et al., 2022; Ludeke et al., 2019; Lee & Ashton, 2012; Zhao et al., 2016). Hence, we theorize that:

H10B_1-H10B_9: *Honesty-Humility will moderate the relationship between each of the OGD-related Nine technology adoption factors and Behavioral Intention such that the relationship is stronger for individuals with higher Honesty-Humility*.

Emotionality. Neurotics are vulnerable and tend to become angry and worrisome easily-this is characteristic of the emotionality dimension. Extant literature underlines that individuals scoring high on the neuroticism dimension are found lacking in motivation to learn (Major, Turner & Fletcher, 2006) which makes them repulsive to having a learning goal orientation (Payne, Youngcourt & Beaubien, 2007). Another study attests that those individuals ranking high on neuroticism will feel more anxious to use new facilities thereby finding it more secure to use new technology (Wang & Yang, 2005). Neuroticism had a *direct* negative effect on both the perceived and actual use of technology (Barnett et al., 2014). Thus, following this logic, that individuals with higher levels of neuroticism tend to be less receptive to new experiences (Watjatrakul, 2016), it may be deduced that individuals scoring low on the Emotionality trait are likely to adopt and use OGD. Our hypotheses follow that:

H11A: *Emotionality will be negatively associated with Behavioral Intention to adopt and use OGD*.

However, According to Devaraj et al. (2008), neuroticism is linked to negative beliefs about the usefulness of technology. Neurotic individuals tend to perceive technological advancements in their work as threatening and stressful, which leads to negative views about the usefulness of technology. Neuroticism also has been found to negatively affect Performance Expectancy, Effort Expectancy and Facilitating Conditions (Ramirez-Correa et al., 2019; Lakhal & Khechine, 2017; Boontarig, 2016; Svendsen et al., 2013; Tran, 2016). Based on these findings, we can hypothesize the presence of an *indirect* significant effect of Emotionality in the context of OGD adoption and use, namely:

H11B_1-11B_9: *Emotionality will be negatively associated with each of the OGD-related Nine* technology *adoption factors*.

Neurotic individuals tend to adopt emotion-focused coping strategies (Wills et al., 2001). Therefore, when faced with a problem or negative outcomes resulting from their technology use, they seek ways to rationalize their actions and alleviate negative emotions, rather than addressing the underlying behavior (Vaghefi & Qahri-Saremi, 2018). In addition, the findings from extant literature about the presence of a significant negative *moderating* effect of neuroticism on internet experience (defined as the capability of using the internet) the facilitating conditions-intention relationship (Wang & Yang, 2005); on a perceived emotional value on intention to study online courses (Watjatrakul, 2020); intention to use 5G technology (Irfan, & Ahmad, 2022), motivate us to put forward the following hypothesis:

H11C_1-11C_9: *Emotionality will moderate the relationship between each of OGD-related Nine technology adoption factors and Behavioral Intention such that the relationship is stronger for individuals with lower Emotionality*.

eXtraversion. Extraversion is marked by low emotional stimulation and this may be linked to the fact that external sources of stimuli are pertinent for extrovert individuals (Eysenck, 1967, 1973). This trait is associated with increased social interaction activities of an individual. This fact has been attested in the extant literature that extroverts are better performers when it comes to working in groups or on tasks that mandate interaction with others (Mount, Barrick & Stewart, 1998). Svendsen et al. (2013) found that extraversion influenced behavioral intention (BI) both *directly* and mediated through the TAM beliefs. Therefore, first of all, we want to test our hypothesis that that individuals with higher extraversion scores are more likely to accept and use OGD than their counterparts. Hence, we theorize that:

H12A. *eXtraversion will be positively associated with Behavioral Intention to adopt and use OGD*.

Prior research also has shown that, extraversion is positively related to the attitude to use technology, facilitating condition, intention to use, perceived usefulness, perceived ease of use, social influence and trust (Conti, Commodari & Buono, 2017; Wang et al., 2020; Tran, 2016; Chipeva, 2018; Irfan, & Ahmad, 2022) and there seems to be a correlation between increasingly extroverted

[1] Here and below: *Nine technology adoption factors* ={*Performance expectancy; Effort Expectancy; Social Influence; Facilitating Conditions; Voluntariness of Use; System Quality; Information Quality; Data Quality; Trust*}.

individuals and their enjoyment of challenging situations commonly found in various gaming genres (Teng, 2008). Accordingly, we hypothesize that:

H12B_1-H12B_9: *eXtraversion will be positively associated with each of the OGD-related Nine technology adoption factors*.

Moreover, extraversion positively *moderates* the relationship between training and perceived usefulness (Li, 2016); and subjective norms and intention to use (Devaraj et al., 2008). Additionally, extraversion positively moderates the relationships between expected visibility and attitude toward using smartwatches; and between expected self-expressiveness and attitude toward using smartwatches (Krey, 2019). Therefore, we expect that when extraversion is higher, the effect of technology adoption factors on Behavioral Intention to adopt and use OGD increases. To formally hypothesize:

H12C_1-H12C_9: *eXtraversion will moderate the relationship between each of the OGD-related Nine technology adoption factors and Behavioral Intention such that the relationship is stronger for individuals with higher eXtraversion.*

Agreeableness. One of the dimensions of agreeableness relates to the tendency to sacrifice one's own pleasures to please others (Narayanan, Menon & Levine, 1995). Furthermore, agreeableness measures the degree of trust, straightforwardness and tender-mindedness. Agreeableness did not have any relation with the perceived or actual usage of the IT system (Barnett et al., 2014). Agreeable individuals tend to perceive technology as more useful, as they are accommodating and cooperative when evaluating new technology. They prioritize the positive and cooperative aspects of technology over factors that might hinder performance (Devaraj et al., 2008). Highly agreeable personalities are more likely to report higher levels of expertise, enjoyment, and control in video games (Johnson et al., 2012); agreeable students are prone to experiencing a sense of playfulness in virtual reality (VR) learning systems (Wang et al., 2022) So, we need to know if will the same behavior spread to their intention to adopt and use OGD. Accordingly, we investigate whether agreeable individuals are more likely to adopt and use OGD and hypotheses that:

H13A: *Agreeableness will be positively associated with Behavioral Intention to adopt and use OGD*.

However, in other research agreeableness positively affects effort expectancy (specifically true for males but not significant for females) thereby easing the usage of technology (Lakhal & Khechine, 2017); individual ICT usage behavior (Chipeva, 2018); perceived ease of use VR-based learning systems (Wang et al., 2022); intention to use 5G technology (Irfan, & Ahmad, 2022). Consequently, the following hypothesis was formulated:

H13B_1-H13B_9: *Agreeableness will be positively associated with each of OGD-related Nine technology adoption factors*.

Additionally, prior research contends that agreeableness positively *moderates* the social influence-intention relationship to use internet (Wang & Yang, 2005); relationship between behavioral intent and extent of security software use (Shropshire, 2015). Therefore, this research tends to investigate the role of agreeableness as a moderator of the OGD-related intention–behavior relationship:

H13B_1-H13B_9: *Agreeableness will moderate the relationship between each of OGD-related Nine technology adoption factors and Behavioral Intention such that the relationship is stronger for individuals with higher Agreeableness*.

Conscientiousness. Individuals scoring high on this trait are considered to be dependable and responsible apart from their strong focus on achievement. This last trait propels individuals to set goals and engage in behaviors that help them to succeed in diverse contexts (Major, Turner & Fletcher, 2006). Previous research showed how conscientiousness had a direct positive effect on both perceived and actual use of the IT system (Barnett et al., 2014). Specifically, conscientiousness was positively associated with both perceived and actual use of the IT system use (Barnett et al., 2014). Thus, it is likely that those scoring high on the conscientiousness traits will adopt and use OGD in contrast with the others. Thus, we hypothesize that:

H14A: *Conscientiousness will be positively associated with Behavioral Intention to adopt and use OGD*.

On the other hand, conscientiousness was found to impact the relationship between facilitating conditions, perceived value and intention to use a technology (Boontarig, 2016). Performance Expectancy was found to be more important for least conscientiousness individuals to facilitate technology usage (Ramirez-Correa et al., 2019). Conscientious person is likely to recognize the benefits of e-learning, such as time-saving, flexibility, and overall usefulness (Punnoose, 2012); and positively perceive the easiness of using VR-based learning systems (Wang et al., 2022) and social networking technology (Rosen & Kluemper, 2008). Therefore, we expect that:

H14B_1-H14B_9: *Conscientiousness will be positively associated with each of OGD-related Nine technology adoption factors*.

Moreover, prior research has shown that conscientiousness positively moderates the relationship between behavioral intent and extent of security software use (Shropshire, 2015); students' pro-ecological behavioral intention to practice Green IT (Dalvi-Esfahani, 2020). Therefore, we expect that when conscientiousness is higher, the effect of technology adoption factors on Behavioral Intention to adopt and use OGD increases. To formally hypothesize:

H14C_1-H14C_9: *Conscientiousness will moderate the relationship between each of OGD-related Nine technology adoption factors and Behavioral Intention such that the relationship is stronger for individuals with higher Conscientiousness*.

Openness to Experience. Openness to experience is linked with an individual's propensity to try novel and unique things which sets them apart from the others (Devaraj et al., 2008). Individuals who are open to new experiences tend to be more creative, willing to explore unconventional ideas, and demonstrate higher intellectual and mental abilities. As a result, they are independent thinkers and less easily swayed by external influences (Sharm & Citurs, 2004). Openness was found to have a direct positive effect on technology usage (Maican et al., 2019; Conti et al., 2017); consumers' desire to adopt green energy technologies (Zeng et al., 2022) and internet usage (McElroy et al., 2007). Opened to experience students are likely to perceive the e-learning system as more useful and easier to use (Svendsen et al., 2013), and VR-based learning systems - innovative, sophisticated, and thrilling (Wang et al., 2022). Based on these findings, we hypothesize that as a personality trait focused on the extent to which an individual is receptive to experiences, higher scores for Openness to Experience shall likely translate to an increased propensity to adopt and use OGD. Hence, we hypothesize the following:

H15A: *Openness to Experience will be positively associated with Behavioral Intention to adopt and use OGD.*

Prior research also has shown that, Openness to experience affects adoption of renewable energy technology (He & Veronesi, 2017), cloud computing (Aharony, 2015) or MOOCs (Wu & Chen, 2017) through the perceived ease of use; and has an effect on performance expectancy in mobile easy payment (Lee et al., 2016). Watjatrakul (2016) observed that they paid more attention to the quality of online learning system. Based on these findings, we can hypothesize the presence of an *indirect* significant effect of Openness to experience in the context of OGD adoption and use, namely:

H15B_1-H15B_9: *Openness to Experience will be positively associated with each of OGD-related Nine technology adoption factors.*

Moreover, openness has been found to have a significant positive moderation effect on the association between social media use for COVID-19 vaccine information and intention to receive the COVID-19 vaccination (Mo, 2021). Findings of the (Ashrafi, 2022) study highlighted the moderating effect of OE in predicting the correlation between passengers' willingness to use Ride-sharing services and their overall value perception. Therefore, we expect that when Openness to Experience is higher, the effect of technology adoption factors on Behavioral Intention to adopt and use OGD increases. This concern has yet to be investigated in literature and, therefore, the following hypothesis was proposed:

H15C_1-H15C_9: *Openness to Experience will moderate the relationship between each of OGD-related Nine technology adoption factors and Behavioral Intention such that the relationship is stronger for individuals with higher Openness to Experience.*

3. Methodology

This section aims to describe the methodology adopted in the current study. Method-wise, a three-fold triangulation approach was used. *First*, the literature available on how personality might impact the UTAUT relationships was conducted with the aim (i) to study the types of models applied and the measurement constructs designed; (ii) to identify the research gap; and (iii) to guide our research models development. *Second*, to assess how strong the impact of personality traits on the behavioural intention to use OGD, the respondent's knowledge was used. As the method of inquiry, we chose an online expert questionnaire to collect data. *Third*, we used the set of structural equation models to investigate the direct influence and the moderating effects of personality traits on the behavioural intention to use OGD. Section 3.1 provides information on related models. Section 3.2. introduces the process of measurement instrument development including sampling and data collection. Section 3.3 describes the data analysis methods. Section 3.4 presents the strategy of experiments on the different models and the reasons for the final model definition.

3.1. Measurement development and data collection

For measurement instrument development the constructs from (i) adapted UTAUT (Table 1) and (ii) HEXACO-100 inventory models were used. All instrument items and a complete set of questions can be found in Appendix 3. The questionnaire was developed and used to test the measurement instrument and to collect the primary data. The questionnaire was divided into three parts. The *first* part of the questionnaire captured the demographic details such as gender, age, education level, year of study, and fields of study of individual respondents. The *second* part of the questionnaire captured user behavioral intentions to use Open Government Data. For each latent construct, three to four questions (indicators) were formulated to capture the usage and adoption of OGD. All the reflective indicators were measured on a 5-point Likert scale using scales from "strongly disagree" to "strongly agree". The *third* part of the questionnaire aimed to assess the personality using a self-report inventory. The six personality factors were measured through a series of questions designed to rate an individual on the levels of each factor. Some of the questions (indicators) from the HEXACO model have the reversed scale (R), where 5 means "strongly disagree", but the score of 1 means "strongly agree".

Students who are actual or potential "academics/users", who can use data for their own research objectives and various professional needs, and represent a variety of fields of study and OGD-specific needs and skills, were selected as a primary targeted population for our study. The rationale for administering the research instrument among university students is that the academic sector presents one major potential group for OGD use and adoption (Borgman, 2015; Golub & Lund, 2021), and youth is one of the most promising target audiences for promoting an open government culture and including youth as active participants in open government strategies and initiatives (OECD, 2016). The choice of this sample also was driven by convenience and constraints imposed by limited

Table 2
Demographic characteristics of the respondents (n = 530).

Gender	#	%	Age	#	%
Female	247	46.6	16–20 years	332	62.6
Male	283	53.4	21–25 years	190	35.8
Education	#	%	26–30 years	5	0.9
Bachelor's	500	94.3	Above 30 years	3	0.6
Master's/PhD/PostDoc	30	5.7	Field of study	#	%
Year of study	#	%	Humanities and Social Sciences	111	20.9
1st year	59	11.1	Law	44	8.3
2nd year	37	7.0	Management/Commerce	74	14.0
3rd year	269	50.8	Nursing/Medical	6	1.1
4th year	157	29.6	Engineering	217	40.9
5th year	3	0.6	Hospitality/Hotel Management	41	7.7
Other	5	0.9	Other	37	7.0

research funding.

We used an online survey instrument (Google Form) to collect data. All measurement items were presented in English. A link to the survey instrument was distributed online (via email and WhatsApp) after explaining the research purpose to the students (specifically, only the actual OGD users) of a private university in India. Recipients of the link were invited both to complete the survey and to give their e-mail addresses in case they are interested in the results of this study. Over six months in 2022, we received 530 valid responses. A series of t-tests were conducted to test for any significant differences between the usable responses in the first period and the second period. No significant differences were found. The demographic characteristics of the respondents are described in Table 2 given below.

3.2. Data analysis

The Partial Least Square (PLS) method using SmartPLS 3.3.9 software (Ringle, Wende, & Will, 2005) was applied to test the direct influence or the moderating effects of personality traits on the behavioral intention to use Open Government Data. A two-stage approach was applied to study each research model. *First*, assessing the quality of the measurements using the measurement model. *Second*, testing the hypotheses using the structural model.

3.3. Experiments strategy

To explain the context of the influence of personal trials on the use and adoption of Open Government Data, two experimental steps were realized:

Step 1. Developing three research models to consequently investigate how and to what extent personality traits (i) *directly*; (ii) *indirectly*, and (iii) as a *moderator* affect the behavioral intention to use and adopt OGD. The result of this stage should be a sample of personality traits that demonstrate their *significant* impact on behavioral intention to use and adopt OGD, performing the role of a direct, indirect or/and moderating factor.

Research Model 1. Examines the *direct* effects of HEXACO personality traits on users' behavioral intention to use OGD in the future. Uses an adapted UTAUT as the underlying OGD adoption model. As shown in Fig. 1, we test the (i) contextual hypotheses outgoing from UTAUT (H1-H9); and (ii) hypotheses linking personality traits (H10A-H15A) to behavioral intentions.

Research Model 2. Examines the *indirect* effects of personality traits (HEXACO) on users' behavioral intention to use OGD through the user's technology adoption (adapted UTAUT). As shown in Fig. 2, we test the (i) hypotheses direct linking the personality traits to each of OGD adoption factors (H10B-H15B) and (ii) contextual hypotheses outgoing from users' technology adoption factors (H1-H9)

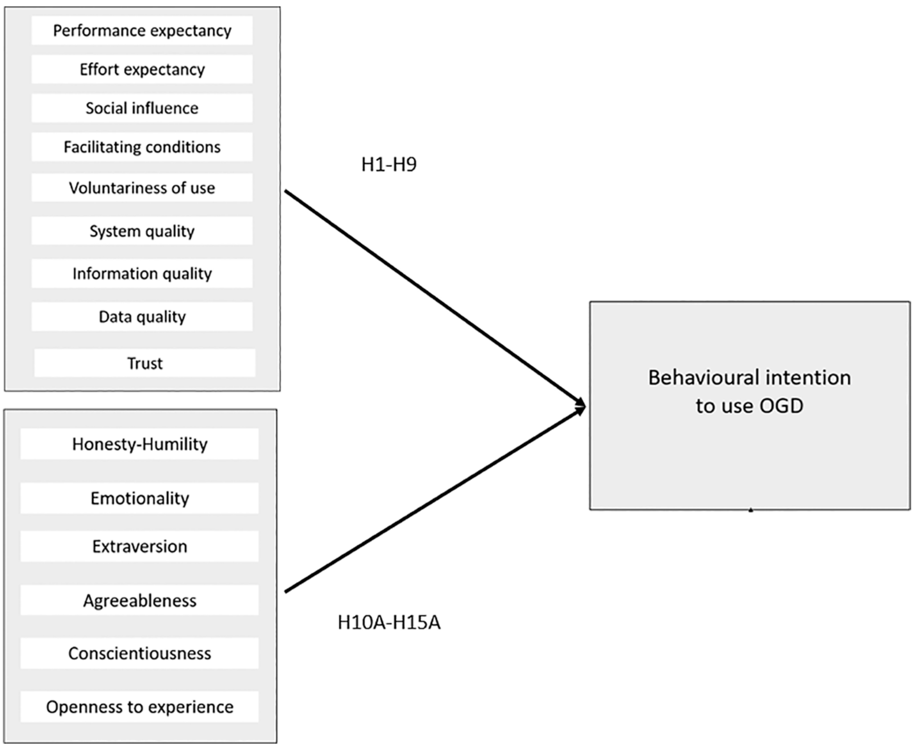

Fig. 1. Research Model 1 (RM1) – Direct effect of OGD adoption (adapted UTAUT model) and personality traits (HEXACO) (()).
adapted from Abu-Shanab, Pearson & Setterstrom, 2010; Conti, Commodari & Buono, 2017

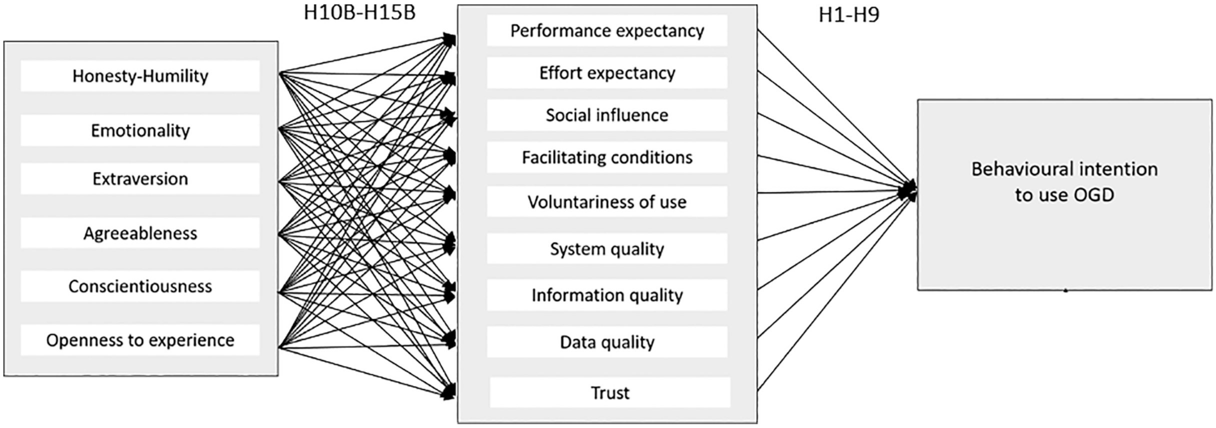

Fig. 2. Research Model 2 (RM2) – Indirect effect of personality traits on behavioral intention to use OGD thought users technology adoption (()). adapted from Lakhal & Khechine (2017

that to behavioral intentions to use OGD in the future.

Research Model 3. Examines how HEXACO personality traits *moderate* the effect of adapted technology adoption model factors on users' behavioral intention to use OGD. As shown in Fig. 3, we test hypotheses linking the influence of personality traits (H10C-H15C) on the relationship between each of the UTAUT adoption model factors (H1-H9) and behavioral intention.

Step 2. Building and exploring the Final Research Model that (i) aim to explain the *comprehensive* nature of the influence of personal trials on the use and adoption of OGD, and (ii) includes the selected *significant* direct, indirect, and moderating effects identified in step 1.

4. Results and findings

4.1. Models testing

4.1.1. Measurement model assessment

According to the methodology, firstly, we evaluated the reflective *measurement* model (Appendix 3). *Individual indicator reliability*

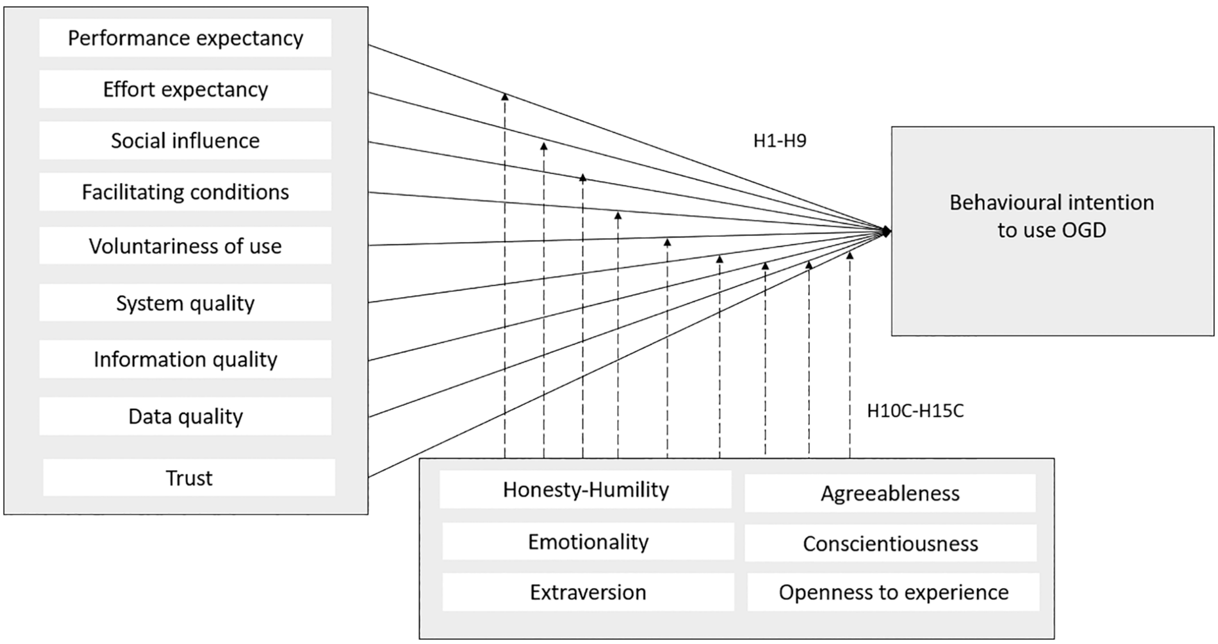

Fig. 3. Research Model 3 (RM3) – Moderating effect of HEXACO personality traits on technology adoption influence on behavioral intention to use OGD in the future (()).
adapted from Boontarig, 2016

(outer loadings) values in all three Research models achieved the recommended loading values of > 0.708 (Hair et al., 2019) for all 35 items from the UTAUT-related part of the construct. In turn, 79 (for RM_1 and RM_3) and 76 (for RM_2) out of 96 items from the HEXACO-related part of the construct exceeded the (>0.4) threshold (Hulland, 1999). The loadings values of the three Research models are included in Appendix 4. The *internal consistency* reliability is assessed using Cronbach's alpha (α) and Composite Reliability (CR). The α and CR values for all constructs shave good internal consistencies, the reliability ranging from 0.778 to 0.9 for the α; and 0.711 to 0.955 for the CR (see Appendix 5). Thus the model can be considered reliable. All constructs from UTAUT-related par demonstrate good *convergent validity* which explains more than 50 % of the variance (Hair et al., 2019). For all HEXACO-related part constructs AVE scores dropped to values below 0.50 (see Appendix 5). Concerning *discriminant validity,* the results, presented in Appendix 5 confirm that: (i) all constructs from the UTAUT-related part demonstrate values of the outer loading were above the values of all their cross-loadings on the other constructs.; (ii) in 16 out of 96 constructs from the HEXACO-related part indicators' the cases were found where the indicator's loadings on its own construct are lower than its cross-loadings with other constructs (Henseler, Ringle, & Sarstedt, 2015) (see Appendix 6).

4.1.2. Structural models analysis

The examination of the *structural* model was carried out to test the hypotheses put forward in the process of building the research model. A bootstrapping procedure with 5000 iterations was performed to examine the statistical significance of the weights of sub-constructs and the path coefficients (β).

Research Model 1. Appendix 7 provides the Research Model 1 estimation results. The standard deviation (STDEV) of path coefficients is estimated from the original sample (O) and samples obtained from bootstrapping process (M) to confirm the statistical significance of hypotheses of *direct* effect (*H1–H9, H10A-H15A*) and the direction of either positive or negative and results. Out of the fifteen (15) hypotheses, five (5) are supported. *Behavioural Intention* (BI) to use OGD is significantly strongly positively affected by *Trust* (H9: $\beta = 0.61$, $p < 0.01$) and weekly positively affected *Performance Expectancy* (H1: $\beta = 0.095$, $p < 0.05$) technology adoption factors, substantially explaining 75.6 % of the variance in the dependent variable. *None* of the *personality* traits has a direct significant impact on behavioral intention to use and adopt OGD. RM_1 demonstrates a substantial level of $R^2 = 0.756$. SmartPLS output of the Research Model 1 estimation is presented in Appendix 8.

Research Model 2. Examining the *structural* model of Research model 2 was carried out to test the *indirect* effects of personality traits (*H10B-H15B*) and the main direct effects of technology adoption factors (*H1–H9*). Appendix 9 presents the summary of the hypotheses tests. Regarding the direct effects of the UTAUT constructs on Behavioral Intention to adopt and use OGD, two out of the nine hypotheses were supported. *Trust* was found to be a strong predictor of the Behavioral Intention (H9: $\beta = 0.617$, $p < 0.01$) and similar positively significant results were secured for Performance Expectancy (H1: $\beta = 0.09$, $p < 0.05$), substantially explaining 75.1 % of the variance in the dependent variable. Changes in the degree of effect of these factors on BI compared to RM_1 are insignificant.

Regarding the *indirect* effects of the HEXACO traits, fourteen (14) out of the 54 hypotheses were supported. Our results show *first*, that *Openness to Experience* personal trial is significantly positively mediated by Performance Expectancy (H15B_1: $\beta = 0.369$, $p < 0.01$), Effort Expectancy (H15B_2: $\beta = 0.383$, $p < 0.01$), Social Influence (H15B_3: $\beta = 0.327$, $p < 0.01$), Facilitating Conditions (H15B_4: $\beta = 0.465$, $p < 0.01$), Information Quality (H15B_7: $\beta = 0.295$, $p < 0.01$) and Trust (H15B_9: $\beta = 0.191$, $p < 0.05$). So, we can conclude that open to new experience individuals more likely to view OGD technology as useful (Performance Expectancy) and easier to use (Effort Expectancy); will probably find more people that have adopted or are thinking of adopting OGD (Social Influence); will perceive greater facilitating conditions and information quality of used OGD (Facilitating Conditions and Information Quality); and will tend to have higher trust toward OGD technology (Trust).

Second, the *Conscientiousness* is significantly positively mediated by System Quality (H14B_6: $\beta = 0.185$, $p < 0.05$), Information Quality (H14B_7: $\beta = 0.179$, $p < 0.05$), Data Quality (H14B_8: $\beta = 0.212$, $p < 0.05$); and also Trust (H14B_9: $\beta = 0.191$, $p < 0.05$) to Open Government Data. It shows that conscientious individuals just like open to new experience individuals will tend to have higher trust toward OGD technology (Trust) and more likely to view the greater information quality of used OGD (Facilitating Conditions and Information Quality); but also more perceive a higher quality of OGD technology data and system itself (System Quality and Data Quality).

Third, the *Emotionality* is significantly negatively mediated by System Quality (H10B_6: $\beta = -0.213$, $p < 0.05$); and Information Quality (H11B_7: $\beta = -0.222$, $p < 0.05$) perception. So, highly emotional individuals can tend to seek more problems in OGD data and system quality (System Quality and Data Quality).

Fourth, the *Agreeableness* is significantly positively mediated by Social Influence (H13B_3: $\beta = 0.211$, $p < 0.05$); and Voluntariness of Use OGD (H13B_6: $\beta = 0.278$, $p < 0.01$). So, we can conclude that Agreeable people just like open to new experience will probably find more people that have adopted or are thinking of adopting OGD (Social Influence), but also they will be more enthusiastic about the use of OGD as voluntary.

RM_2 shows a substantial level of $R^2 = 0.751$ but is lower than for RM_1. SmartPLS output of the Research Model 2 estimation is presented in Appendix 10.

Research Model 3. Examining the *structural* model of Research model 3 was carried out to test the moderation effects of personality traits (*H10C–H15C*) and the main direct effects of technology adoption factors (*H1-H9*). Appendix 11 presents the RM_3 estimation results. BI to use OGD is very strongly positively affected by Trust (H9: $\beta = 0.669$, $p < 0.01$) and also positively affected by Performance Expectancy (H1: $\beta = 0.118$, $p < 0.05$), substantially explaining 78.5 % of the variance in the dependent variable. The degree of the positive effect of Trust on BI was significantly reduced compared to RM_2; the degree of influence of Expected Performance on BI has increased significantly compared to RM_2.

Regarding the *moderating* effects of the HEXACO traits, three out of the 54 hypotheses were supported. Our results show *first*, that relationship between *Information Quality* and Behavioral Intention to adopt and use OGD was positively moderated by *Honesty-Humility* (H10C_7: $\beta = 0.239$, $p < 0.05$). This could be explained by the fact that respondents with a *higher* level of propensities of being fair, honest and humble being as against her being manipulative, pretentious and materialistic, as we expected, have a *stronger* positive effect of Information Quality on BI to adopt and use OGD. *Second*, the relationship between *Information Quality* and Behavioral Intention was negatively moderated by *Extraversion* (H12C_7: $\beta = -0.251$, $p < 0.05$). This means that respondents with a *higher* level of outgoing, assertive, sociable and demonstrative, contrary to our expectations, have a *weaker* positive effect of *Information Quality* on BI to adopt and use OGD. *Third*, we found that *Extraversion* also was found to have a significant positive moderating impact on the relationship between *Trust* and Behavioral Intention to adopt and use OGD relationship (H12C_9: $\beta = 0.320$, $p < 0.05$). This means that respondents with a *higher* level of extraversion personality traits have a *stronger* positive effect of *Information Quality* on *BI* to adopt and use OGD (Appendix 12). Other 51 moderating effects as hypothesized earlier were statistically insignificant. RM_3 shows a substantial level of $R^2 = 0.813$ and much increase over RM_1 and RM_2. SmartPLS output of the Research Model 3 estimation is presented in Appendix 13.

4.2. Combined model

At this stage of our study, according to our methodology, the aimed to build and explore the Final Research Model which (i) helps to extend the understanding of the comprehensive nature of the personal trial's impact on the use and adoption of OGD; and (ii) is suggested to be built based on selected *significant* direct, indirect, and moderating effects, that were identified during Research Models 1, 2 and 3 exploring (Table 3). As shown in Fig. 4, we test the following hypotheses:

Examining the *structural* model of constructed Final Model was carried out to test the *indirect* and *moderating* effects of personality traits; and the main direct effects of technology adoption factors (Table 3). Out of the 26 hypotheses, fourteen (14) are supported. As a result of estimating the Final model were confirmed the following hypotheses of direct effects of the UTAUT constructs on the Behavioral Intention to adopt and use OGD: BI to use OGD is very strongly positively affected by *Trusts* (H9: $\beta = 0.603$, $p < 0.01$) and also positively affected by *Performance Expectancy* (H1: $\beta = 0.098$, $p < 0.05$), substantially explaining 75.6 % of the variance in the dependent variable. The degree of the positive effects of Trust and Performance Expectancy on BI are significantly reduced compared to RM_1. Regarding the *indirect* effects of the HEXACO traits, the Final model shows the following: (1) *Openness to Experience* has confirmed all significant positive effect on Performance Expectancy (H15B_1: $\beta = 0.437$, $p < 0.01$), Effort Expectancy (H15B_2: $\beta = 0.419$, $p < 0.01$), Social Influence (H15B_3: $\beta = 0.293$, $p < 0.01$), Facilitating Conditions (H15B_4: $\beta = 0.455$, $p < 0.01$), Information Quality (H15B_7: $\beta = 0.328$, $p < 0.01$) and Trust (H15B_9: $\beta = 0.219$, $p < 0.01$). (2) *Conscientiousness* has confirmed three out of four significant positive effects on the level of an individual's perception of OGD System Quality (H14B_6: $\beta = 0.379$, $p < 0.01$), Information Quality (H14B_7: $\beta = 0.226$, $p < 0.01$), and Data Quality (H14B_8: $\beta = 0.278$, $p < 0.01$). (3) *Emotionality* has confirmed its significant negative impact on OGD System Quality (H11B_6: $\beta = -0.155$, $p < 0.01$) and on Information Quality (H11B_7: $\beta = -0.208$, $p < 0.01$). (4) *Agreeableness* has confirmed significant positive impact only on Social Influence (H13B_3: $\beta = 0.182$, $p < 0.01$). The degree of the positive effects of Openness to Experience on most of these factors (except Social Influence) significantly increased compared to RM_2.

Table 3
Significant personality traits factors affecting behavioral intention to use OGD.

Path	H	Research Model 1 $R^2 = 0.756$	Research Model 2 $R^2 = 0.751$	Research Model 3 $R^2 = 0.813$	Final Model $R^2 = 0.756$
Personality traits directly affecting behavioral intention to use OGD					
Not identified	H10A-H15A	–	–	–	–
Personality traits indirectly affect behavioral intention to use OGD through user's technology adoption					
Emotionality -> System Quality	H11B_6	–	−0.213*	–	−0.155*
Emotionality -> Information Quality	H11B_7	–	−0.222*	–	−0.208**
Agreeableness -> Social Influence	H13B_3	–	0.211*	–	0.049 (ns)
Agreeableness -> Voluntariness of Use	H13B_5	–	0.278**	–	0.182**
Conscientiousness -> System Quality	H14B_6	–	0.185*	–	0.379**
Conscientiousness -> Information Quality	H14B_7	–	0.179*	–	0.226**
Conscientiousness -> Data Quality	H14B_8	–	0.212*	–	0.278**
Conscientiousness -> Trust	H14B_9	–	0.191*	–	0.099 (ns)
Openness to Experience -> Performance Expectancy	H15B_1	–	0.369**	–	0.437**
Openness to Experience -> Effort Expectancy	H15B_2	–	0.383**	–	0.419**
Openness to Experience -> Social Influence	H15B_3	–	0.327**	–	0.293**
Openness to Experience -> Facilitating Conditions	H15B_4	–	0.465**	–	0.455**
Openness to Experience -> Information Quality	H15B_7	–	0.295**	–	0.328**
Openness to Experience -> Trust	H15B_9	–	0.191*	–	0.219**
Personality traits moderating the user's technology adoption affect behavioral intention to use OGD through user's technology adoption					
Honesty–Humility*Information Quality -> BI	H10C_7	–	–	0.239*	0.022 (ns)
eXtraversion*Information Quality -> BI	H12C_7	–	–	−0.251*	−0.013 (ns)
eXtraversion*Trust -> BI	H12C_9	–	–	0.320*	−0.039 (ns)
User's technology adoption direct effect on behavioral intention to use OGD through user's technology adoption					
Performance Expectancy -> BI	H1	0.101*	0.090*	0.118*	0.098*
Trust -> BI	H9	0.686**	0.617**	0.559**	0.603**
Sig. *p < 0.05; **p < 0.01; ns: not significant					

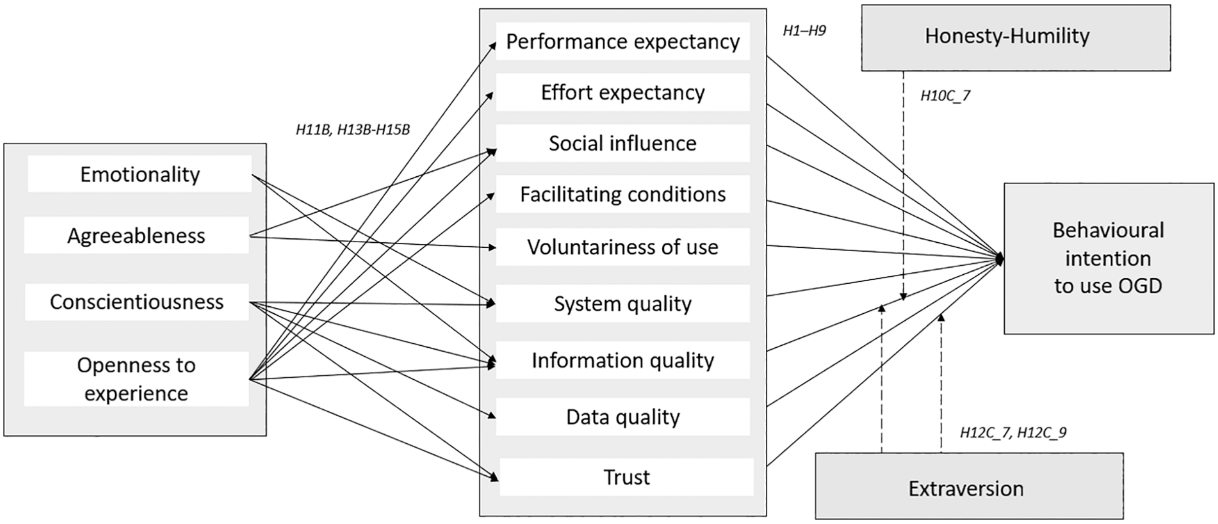

Fig. 4. Final Model (FM) – Combined indirect and moderating effect of HEXACO personality traits on technology adoption impact on behavioral intention to use OGD in the future.

Hypotheses H13B_3 and H14B_9 were not supported.

None of the hypotheses about personality traits' *moderation* effect was confirmed (H10C_7, H12C_7 and H12C_9).

The Combined model has $R^2 = 0.756$. It has not exceeded the level of the RM_3, but still presents a significant substantial level including also all the constructs that indirectly affect the dependent variables which are recognised as important in the previous experiments. Since the combined model incorporates the knowledge of all the previous ones, it needs to be further evaluated against RM_3 results with new data. The summary of all four Research models' results is presented in Table 3.

The final personality traits influence Open Government Data (OGD) adoption and usage model as shown in Fig. 5 below:

5. Discussion and implications

5.1. Theoretical implication

The theoretical implications of our study are primarily to further expand the use of UTAUT frameworks, constructs, and related elements to understand the adoption of OGDs and open data portals, taking into account the users' personality traits, to help create

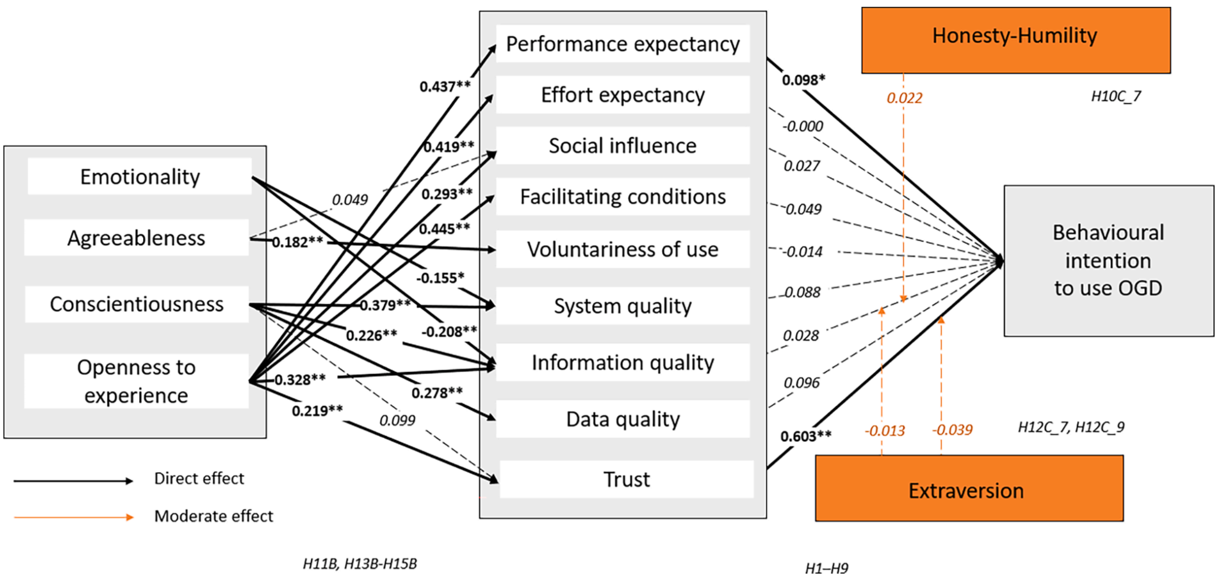

Fig. 5. Path coefficients of the final bootstrapped model (*p < 0.05; **p < 0.01).

conditions for stakeholders with different psycho types and individual reactions to technology to effectively reuse OGD. The main contribution of our study to the existing literature on OGD adoption is that we provided a deeper understanding of the nature of personality traits' impact on the behavioral intention to use and adopt Open Government Data in the context of students' perception.

Before discussing our results regarding the personality traits, we should note that our study confirmed that, *Performance Expectancy*, had positive direct effects on BI to use the OGD (Saxena & Janssen, 2017; Talukder et al., 2019; Zainal, et al., 2022). In the context of India, the findings provide valuable insight into the underlying motivations of OGD users. It is becoming evident that users, especially young people, have high hopes for OGD to improve their performance and promote professional growth (Saxena & Janssen, 2017; Kassen, 2018; Alawadhi & Morris, 2008). In the responses collected, 45.77 per cent of participants conveyed that OGD holds importance to them (Appendix 12). Moreover, professional curiosity and the opportunity to network with other industry peers are seen as one of the most important motivations for joining the open data movement (Vieira & Alvaro, 2018). This behaviour is especially popular among students of technological universities. Understanding this key motivation can guide policymakers and stakeholders in designing and implementing OGD initiatives that meet the specific needs and aspirations of users in India. By focusing on initiatives that match the interests and career expectations of different types of users, decision-makers can promote the adoption and use of OGDs, producing positive socioeconomic impacts and supporting the country's overall development goals.

Also, we proved that *Trust* is the strongest positive predictor of user intention to continue using new technology (Abu-Shanab, Pearson & Setterstrom, 2010; Bélanger & Carter, 2008), and particular OGD (Purwanto, Zuiderwijk, & Janssen, 2020a; Janssen, Charalabidis, & Zuiderwijk, 2012; Lnenicka et al., 2022; de Souza, d'Angelo, & Lima Filho, 2022), and becomes especially important when the technology under investigation involves a potential privacy and security risk to the user (Wiencierz & Lünich, 2022). Indeed, *Trust* is built upon the repeated and reliable use of technology (Almuqrin et al., 2022). In this regard, students are grateful users of OGD, as they are involved in the process of re-using gradually in the learning process; open datasets, as well as the results obtained in the process of their analysis, are carefully checked by professors respected by them; and positive evaluations of their efforts form students' Trust in OGD (Coughlan, 2020). Considering that the dominant group of respondents consisted of 3-4th year students (80.4 %), it suggests that the educational process at Indian universities plays a vital role in motivating students to utilize OGD for their individual and research work. This suggestion is also validated by the responses of the participants, who indicated that after using open data sets for information purposes (23.29 %), the second most common use was for writing academic publications such as projects, reports, or theses (13.23 %) (Appendix 2). Furthermore, these activities were carried out either monthly or several times a month (38.20 %), and weekly or several times a week (36.01 %). The level of trust in university faculty could also contribute significantly to students' understanding of the value of OGD in both their educational journey and future professional development. This emphasis on trust may serve as a primary explanation for the strong significance of the Trust factor as a predictor of OGD adoption and use among the surveyed students.

On the other hand, *Facilitating Conditions* were found as a nonsignificant determinant of intention (Venkatesh et al., 2003; Talukder et al, 2019; Nguyen, 2022; Saxena & Janssen, 2017). As of 2022, India was ranked as the second-largest online market worldwide, trailing only China in terms of internet user population (The Hindu, 2023; Deo & Basrur, 2023). This surge in Internet usage has been evident in both urban and rural areas (India: Number of Internet Users, 2050, 2023). The year 2021 saw rural India even surpass urban areas in terms of internet usage. The considerable increase in rural internet access was mainly due to the expansion of bandwidth, the affordability of data plans, and various initiatives from the government as part of the Digital India campaign.[2] The availability of reliable internet connectivity and well-developed internet infrastructure is the basis for providing users with seamless access to various online resources, including open data sets (Saxena & Janssen, 2017). Indeed, as mentioned above, most of the respondents use open data quite often (weekly or several times a week – 36.01 %), which also indicates that they have free access to the required infrastructure. Moreover, comparing the key statistical indicators of the Indian Open Government Initiative platform (https://data.gov.in/) as presented in the study (Saxena & Janssen, 2017), we see a notable improvement in this OGD initiative development by mid-2023. For instance, the number of resources has grown almost 25-fold. Downloads of OGD have quadrupled. Furthermore, the number of registered users has surged to reach 488,229.[3] Consequently, the lack of significance of the Facilitating Conditions factor in shaping user intentions to continue using OGD is confirmed by all the country-context details provided.

We also identified no relationship between *Effort Expectancy* and perceived BI to use the OGD. In contrast, authors (Lakhal & Khechine, 2017; Saxena & Janssen, 2017; Zainal, 2022) found the presence of a negative impact on effort expectancy, suggesting that data sets are easily available and accessible and less effort is exerted in tapping these data sets. However, our findings are consistent with (Barnett et al., 2014; Lenenicka et al., 2022) and could be explained by the fact that 40.9 per cent of the students surveyed belong to the engineering field of study, hence they definitely have years of web experience (Lee & Hyekyung, 2022) and for them, such technologies as OGDs are by default perceived as easy to use. Furthermore, in studies confirming the significance of Effort Expectancy in determining users' intentions to persist in using OGD (Lakhal & Khechine, 2017; Saxena & Janssen, 2017; Zainal, 2022), the respondents included not just students but also academics, faculty and bureaucrats. This diversity in respondent demographic could influence users' perception of the level of their efforts. As Saxena and Janssen (2017) observed, younger respondents are generally more receptive to the acceptance and utilization of open data. On the other hand, interestingly, the majority of our respondents reported using open data for basic operations, such as learning and exploring (25.38 %), searching and filtering (15.96 %), and selecting and downloading (14.68 %) - tasks that require basic computer and internet skills. More complex operations such as analyzing and linking, visualizing and interacting, evaluating and discussing, providing feedback and reporting, requesting and suggesting, and

[2] https://www.statista.com/statistics/751060/number-of-internet-users-by-region-india/.

[3] https://data.gov.in/analytics.

sharing and publishing were only performed by an average of about 7.33 % of respondents (Appendix 2). This observation could explain why the Effort Expectancy factor doesn't significantly impact the behavioral intention to use Open Government Data – the actual tasks carried out by students may not demand significant effort. But more importantly, these insights indicate a need to enhance students' awareness of the full range of possible actions with open data, as well as to elevate the Indian educational standards related to building students' skills and abilities in the use of OGD.

The notable exception being is our finding about the nonsignificant impact of the *Social Influence* factor on respondents' BI to use OGD (Talukder et al., 2019; Zuiderwijk et al., 2015; Lakhal & Khechine, 2017). But the study (Zainal, et al., 2022) also confirmed those phenomena for academics. These our finding aligns with the reason explained earlier regarding strong significance of the Trust factor for BI to adopt and use OGD. As individuals gain expertise in using OGD, they rely more on their own judgments and perceptions of the dataset's value and the positive outcomes they expect to achieve (Performance Expectancy), and the Trust they place in the data source and the government providing it. The shift in reliance from *external* influences (Social Influence) to *individual* factors can contribute valuable insights into the dynamics of OGD adoption and usage among different user groups, emphasizing the evolving importance of individual factors in shaping users' intention to utilize open data resources effectively. Nevertheless, Indian university authorities should actively promote students to share the Open Data resources they utilize, along with their positive and negative experiences in using and analyzing Open Data on university websites or social media platforms.

The findings related to the insignificance of the three factors characterizing the open government data portals' *Quality*-related indicators on the intention to use OGD open valuable insights. Existing research, such as (Purwanto, Zuiderwijk, & Janssen, 2020a; Talukder et al., 2019; Lnenicka et al., 2022; Alzahrani, 2017), confirmed that indicators of system, information, and data quality are significant in building user's confidence and trust, and had significant effects on OGD adoption. Regarding user satisfaction, sufficiently high information quality, system quality, and service quality also appear as necessary conditions (Gonzálvez-Gallego et al., 2020; Souza et al., 2022). Such observed shift towards building trust in OGD within the context of the chosen country and sample in our study may be a result of the respondents' noticeable emphasis on the perceived value and advantages they can gain from using OGD. However, more probable such findings may indicate a low awareness of users regarding the measures for assessing the quality of the system, data and information, which is consistent with the low professional level of use of open data handling possibilities demonstrated by users and noted in the context of Effort Expectancy. Such insights should serve as a signal to the government that it needs to tighten its control over the quality of services provided through India's OGD portals. Maintaining a balance between promoting the usefulness of data and maintaining data quality is vital so as not to undermine user confidence and reduce the risks associated with the dissemination of misinformation.

Regarding our main personality traits-related findings, the relationships identified in our study (1) partially supported the point of view of the interactional psychology perspective; and (2) demonstrate the additive explanatory effect of situational (UTAUT) and *personality* constructs (HEXACO). Thus, *responding to RQ1*, we found that personality traits do not have a *direct* significant effect on BI to use and implement OGD.

Responding to RQ2, our research contributes to a better understanding of the nature of the personality traits' *indirect* impact on Behavioral intention through the OGD-related technology adoption factors. In more detail, we identified that *Openness to Experience* positively affects Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Information Quality and Trust. Our findings one more time prove that users' openness to new experiences in the OGD context may lead to slightly increased expected effort due to a greater propensity to explore all the features of a system or to conduct a broader search for relevant data (McElroy et al., 2007). This can explain the presence of the insignificant but weakly negative effect of *Effort Expectancy* on behavioral intention to use OGD; strong desire to improve their facilitating conditions allowing them to search, collect, store, analyze and visualize a large amount of OGD. This, in turn can have a direct positive effect on perceived *Performance Expectancy* and OGD technology usefulness (Lee et al., 2016). Moreover, we confirmed, that openness to new experiences positively influences the willingness to find more people that have adopted or are thinking of adopting OGD, and ability to listen to people whose opinions and experiences using OGD are important to them (*Social Influence*), more carefully and inquisitively evaluate and appreciate *Information Quality* (Watjatrakul, 2016), and more *Trust* in such new technologies that bring new knowledge and new opportunities for its application in the future (the second of two significant factors affecting Behavioral Intention directly).

Conscientiousness relationship with BI to use and adopt OGD is significantly mediated by System Quality, Information Quality, Data Quality and Trust. The current study supports the findings of (Nguyen, 2022; Wang & Yang, 2005) where the authors also did not find an effect between Conscientiousness and Effort Expectancy, Facilitating Condition, Social Influence and Performance Expectancy refuting all previous conclusions about this relationship (Lakhal & Khechine, 2017; Boontarig, 2016; Punnoose, 2012). According to our findings, we can suggest, that Conscientiousness, which is characterized by dependability, responsibility, focus on achievement (Major et al., 2006), and is correlated with learning goal orientation (Payne et al., 2007), should also be seen (i) as a factor of increasing user's requirements to the all OGD elements quality (*System Quality, Information Quality, Data Quality*), and (ii) as a factor of direct and positive impact on both the perceived and actual use of the IT system (Barnett et al., 2014; Punnoose, 2012) and on *Trust* if the required OGD quality level is confirmed.

Agreeableness positively affects Social Influence and Voluntariness of Use. Our findings are not consistent with the conclusions of (Lakhal & Khechine, 2017) that found agreeableness positively affects Effort Expectancy and Performance Expectance (Nguyen, 2022; Lakhal & Khechine, 2017; Chipeva et al., 2018) thereby easing the usage of technology. The reasons for Effort Expectancy insignificance in the OGD context have already been explained above. Moreover, one of the dimensions of agreeableness relates to the tendency to sacrifice one's own pleasures to please others (Narayanan et al., 1995), which may well explain the significant effect of agreeableness on the *Voluntariness of Use* OGD. In addition, the assertion that a person whose personality is more pleasant is more open to cooperation and strengthening relationships with people (Devaraj et al., 2008) gives us reason to argue that this personality trait has a positive effect on a person's desire to listen to the opinions of people from his inner circle (*Social Influence*).

Emotionality negatively affects System Quality and Information Quality. Generally, neuroticism was found to be directly and negatively associated with both perceived and actual system use, but not significant for Behavioral Intention (Boontarig, 2016; Barnett et al., 2014). Our findings are not consistent with those (Nguyen, 2022; Wang & Yang, 2005), where neuroticism was found to be negatively associated with Effort Expectancy of the social media detox app and adopting online stocking respectively. Since such factors as System Quality and Information Quality were not previously studied in the context of the influence of personality traits on them, this study's findings can be indirectly explained, by the fact that (i) neurotics prefer to use software and Internet services for communication (Mark & Ganzach; 2014; Wang & Yang, 2005) and (ii) students who are more neurotic are less open to new experience (Watjatrakul, 2016). That is, we can assume that, for neurotics, perceived effort expectancy-related factors are not important, since they are ready to overcome them to limit personal communication in data search and exploring, but the *System Quality* and *Information Quality* being mined will matter, and due to the higher sensitivity of such people, any quality issues can cause a significant negative effect.

Responding to RQ3, our work contributes to advancing theoretical knowledge about the nature of moderating effect that personality traits have on the relationships between technology adoption factors and BI to use and adopt OGD. Higher *Honesty–Humility* psychological traits increase the strength of the positive effect of *Information Quality* on Behavioural Intention to use OGD. Honesty-humility has been documented to be positively related to trustworthiness (Nockur & Pfattheicher, 2021; Pfattheicher & Böhm, 2018), sincere and fair interpersonal and intergroup collaboration (Hilbig et al., 2018; Devaraj et al., 2008; Ramirez-Correa et al., 2019), and decreased cheating behavior (Ścigała et al., 2019; Wang et al., 2022; Ludeke et al., 2019; Lee & Ashton, 2012; Zhao et al., 2016). So, we can explain our findings by the fact that people with a high level of honesty-humility tend to be *truthful*, and their exactingness in terms of a high level of information trustworthiness can indeed positively influence relationships between the effect of Information Quality on BI to use OGD.

We also found that individuals with higher *eXtraversion* personality traits may have a stronger effect of Trust on BI to use OGD. Our findings are inconsistent with (Barnett et al., 2014) indicating that none of the mediation hypotheses supports a significant association between any personality traits and the BI construct; but are consistent with (Furumo et al., 2009; Evans & Revelle, 2008; Chan & Cheung, 2016) who found that extraversion positively predicted *Trust*. Moreover, we determined that individuals with lower extraversion may have a stronger effect on *Information Quality* on BI to use OGD. This finding can be explained by the fact that for people characterized by a low level of sociability, talkativeness, assertiveness, activity and vigor (Oh et al., 2011; Wang & Yang, 2005) will be more significant the possibility of obtaining the necessary, up-to-date, reliable information, which (i) is concentrated on the OGD portal and (ii) does not require additional clarification or enrichment through the use of personality traits with high extraversion.

Responding to RQ4, our work contributes to the development of theoretical knowledge about the nature of the consolidated type of impact of personality traits on the BI to use and adopt OGD. In this stage, we identified that *Trust* and *Performance Expectancy* are stable and strongly positive predictors of BI to use and adopt OGD.

The strongest effect of Personality traits on the Behavioral intention to use and adopt OGD is *indirect*. Thus, *Openness to experience* is the most important personality trait that consistently positively impacts six out of nine (66.67 %) of OGD-related technology adoption factors, such as Trust, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Information Quality. Possession of *Conscientiousness* personality trait enhances the individual's perception of OGD quality-related factors, such as System Quality, Information Quality, and Data Quality. *Agreeable* people are more likely to Voluntarily Use OGD. Excessive *Emotionality* makes people more sensitive to any problems with the System Quality and Information Quality and can cause a significant (not always justified) negative effect on Behavioral intention to use OGD.

In an effort of personality traits to play the *moderating* role, *Honesty–Humility* and *eXtraversion* demonstrated the ability to "maintain", but not "strengthen"/"weaken" the relationships between Behavioral intention and such technology acceptance factors as Information Quality and Trust. That is, this insight gives grounds to assert that *Honesty-Humility* and *eXtraversion* are factors that can ensure the stability of the relationship between Behavioral intention to adopt and use OGD and Information Quality and Trust, preventing them from becoming excessively susceptible to the influence of other personal traits. It is valid when the rest of the personality traits directly affect OGD-related technology adoption factors.

5.2. Practical implication

Based on our findings, we proposed a series of recommendations for practitioners to aimed at harmonizing the actual and potential usage of OGD, factoring in the impact of personality traits on user behavior:

Recommendation 1. The research findings highlight that *Trust* plays a significant role in predicting the adoption and usage of Open Government Data (OGD). Consequently, policymakers should prioritize efforts towards establishing and nurturing trust in the government and its provided data to encourage OGD initiatives' growth. To achieve this, a crucial focus should be on defining clear requirements for Fairness, Accountability, Transparency, Explainability and Ethics of open government datasets (OECD, 2017). Furthermore, policymakers must develop frameworks and guidelines to assess hosted dataset's compliance with these requirements. With specific reference to the Indian case, the study shows that policy managers and executives should first of all ensure that the underlying objectives of OGD initiatives should be fulfilled in terms of provisioning credible and reliable OGD for furthering user engagement.

Recommendation 2. The research identifies *Performance Expectations* as one of the key predictors of OGD adoption and use. In light of this finding, policymakers should prioritize studying the genuine demand for proposed sets of open data. This entails utilizing indicators like the number of views, downloads, showcases, and use cases (Nikiforova et al., 2023) to identify High-Value Datasets that align with users' actual needs and expectations. By focusing on creating datasets that cater to real user requirements, policymakers can enhance the relevance and utilization of OGD initiatives, leading to increased adoption and usage by the public. For instance, for the specific case of Indian academic community, students' engagement with OGD is a function of the latter's relevance for their projects, assignments, general awareness and the like.

Recommendation 3: Based on our study's findings, it is evident that the adoption and intention to use OGD are significantly influenced by personal qualities, particularly *Openness to experience* and *Agreeableness*. In light of this, the Indian government should prioritize efforts to further promote OGD initiatives and raise public awareness about the value, goals, and potential benefits of reusing OGD. By doing so, we can enhance users' openness to new experiences, leading to increased acceptance and utilization of open data (Saxena & Janssen, 2017). Additionally, fostering a culture that highlights the positive impact of using open data on job performance and professional growth, especially among young people, can motivate individuals to actively explore, adapt, and utilize OGD voluntarily. By emphasizing these aspects, the government can effectively encourage OGD adoption and maximize its potential for societal and economic benefits.

Recommendation 4: Building on our study's findings, it is crucial to focus on continuous improvement and enhancement of open data portals' *Quality* features. Particular attention should be given to aspects like System Quality, Information Quality, and Data Quality, as these factors significantly influence the intention of users with high *Consciousness* and *Emotionality* personality traits to accept and use OGD initiatives. By prioritizing the development and planning of OGD initiatives with a strong emphasis on improving these quality features, we can foster a positive user experience and increase the likelihood of OGD adoption among individuals with these specific personality traits.

Recommendation 5: Our study underscores the importance of recognizing the influence of user *personality traits* on OGD preferences and behaviors. In this regards, to expand interest and usage of OGD among users with diverse personality traits, policy makers should to incorporate the provision of highly *personalized* services. This can be achieved through the development of *personalized* functions, catering to the unique needs of users with different personality types (Pakinee & Puritat, 2021). By tailoring the user experience to individual preferences, OGD initiatives can foster higher user engagement and satisfaction.

Recommendation 6: To ensure the success of OGD initiatives in India, it is crucial to align them with the specific vision of government authorities. This alignment should encompass planning, monitoring, and feedback mechanisms to effectively measure and improve the impact of OGD implementations. Additionally, investing in training and development programs for the staff involved in these initiatives is essential to equip them with the necessary skills and knowledge to handle OGD projects proficiently.

5.3. Avenues for research on the OGD adoption

Various research agendas dedicated to the adoption of OGD have already been developed. Some of them focus on discussing the adoption of OGD in a broader theoretical context (Zuiderwijk et al., 2015), focusing on cultural and regional differences (Lenenicka et al., 2022), sustainability and smartness of initiatives (Gao et al., 2023), or different objectives for OGD across different government levels (Yang and Wu, 2016). Our research agenda complements existing agendas by focusing on the relevance of personality traits in shaping the behaviour intention to adopt and use OGD in the future. So, our study suggests several directions for potential future research pathways that could benefit academics and the wider scientific community exploring themes linked to the uptake of OGD initiatives adoption and users behaviour:

Avenue for future research 1: Focus on building multidisciplinary teams by integrating *psychologists* into their collaborations. This should provide an opportunity to identify behavior patterns (Xiao et al., 2020; Xiao et al., 2022) associated with differences in the personal traits of an OGD user, taking into account also national, cultural and other demographic characteristics. It is expected that the obtained insights will help to fill the research gap both (i) in understanding the nature of the diversity of demand for various open datasets; and (ii) in the development of a theory of OGD user behaviour, that is focused not only on the degree of users awareness and their needs, the open data value, its quality, accessibility, thematic diversity (Zuiderwijk et al., 2015; Begany et al., 2021), but also such on internal features as the user's personality traits.

Avenue for future research 2: Consider the deeper investigation of the development of User Experience (UX) design for Open Government Data (OGD) online portals that embed personalized features that cater to the unique needs of different user personality types. This approach is widely used in, for example, the development of a gamified e-learning environment (Pakinee & Puritat, 2021a; Pakinee & Puritat, 2021b; Bennani et al., 2022), as well as the creation of gamified open data portals (Simonofski et al., 2022) for lay (not professional) users, characterized by specific requirements and behavioral features. This research direction could potentially deepen our understanding of how to design adaptive open government data portals; and also augment the concept of ideal portal requirements – encompassing functionality, semantics, and content as suggested by Śaez Martín et al. (2015) – with a new category: personalization requirements related to personality traits.

Avenue for future research 3: Despite user education being a critical component of promotion and facilitating the use of OGD, research on educational programs' current state and prospects is limited (Gascó-Hernández et al., 2018; Papageorgiou et al., 2023). Since our study shows that undergraduate students have mostly basic computer and Internet skills to work with online platforms, this allowed us to conclude that in order to further promote the initiatives of the OGD, scientists and academics need to first all focus on the development of study programs (courses, modules, MOOCs) which are able to comprehensively provide (1) knowledge and skills in using methods and algorithms for open data analyzing; (2) familiarity with the key determinants for assessing the quality of the service provided by open data portals, as well as the quality of open datasets itself; (3) awareness of the core values of using OGD in the context of the chosen field of study, cultural- and country-related characteristics, as well as the interests and expectations of various types of OGD stakeholders. One of the conditions for organizing and conducting such study programs should also be the preliminary testing of the student's personal traits, which will allow teachers or administrators of online courses to adapt the training material and teaching methods, taking into account the student's personality-related behavioral patterns.

Avenue for future research 4: Investigate the possibility to include some other variables in the model to study the behaviour intention to adopt and use OGD For instance, *future* studies may extend our model to appreciate the role of self-efficacy on OGD usage given that *self-efficacy* (an individual's belief that she can perform a specific task) is positively correlated with conscientiousness, agreeableness, openness and extraversion but negatively correlated with neuroticism (Zhang et al., 2019) and it has been shown that self-efficacy is a significant predictor (positive) of the behavioral intention to use technology (Abu-Shanab et al., 2010; Maican et al., 2019). Likewise, *locus of control* (to believe that we have control over the events in life and there is no role of fate or chance on the sequence of events) may be invoked as a possible variable for studying the behavioral intention toward OGD-usage given that locus of control was found to be a significant predictor towards technology usage (Abu-Shanab et al., 2010). Variables like *perceived adaptability* (the perceived ability of technology to be adaptive to the changing needs of the user), perceived enjoyment (feelings of joy or pleasure associated with the usage of technology) and social presence (the experience of sensing a social entity while interacting with a technology) (Conti et al., 2017) may be added to the model advanced in our study for further empirical investigation. Finally, the linkage of behavioral intention to use technology with the variables of *self-determination* theory (motivation) to *autonomy*, *competence* and *relatedness* may be investigated in further research (Osei et al., 2022).

5.4. Limitations of the study

Among the *limitations* of our study, we identified the following: (1) Due to the sampling method used herein (*undergraduate* students), it is difficult to *generalize* the results of the our study to all OGD users in India. But our findings provide insights into the powerful role of personality traits in shaping user's behavioral intention to adopt and use OGD. Therefore, we emphasize the importance of replicating our study involving *all OGD stakeholders*. This would enable a more comprehensive understanding of the subject matter and would further enhance the validation and generalization of our findings; (2) Furthermore, our research cannot be generalized to *non-OGD* users-case in point being the fact that Indian OGD initiative is an emerging one and it is difficult to evaluate its performance as far as usage propensity is concerned. This lends cues for further research to investigate how personality dimensions impact the motivation for OGD usage among non-users; (3) Our study was confined to the context of a single country. Subsequent studies could look into experiences and lessons from several developing nations regarding their use and implementation of OGDs, as well as user adoption. Such research would facilitate a comparative analysis of the distinct experiences encountered by each country. More crucially, these studies could provide a more generalized and holistic view of the unique nature of the impacts of users' personal attributes in developing nations on their intention to use OGD.

6. Conclusion

This study aimed to explore how personality traits explain the behavioral intentions to use OGD by academic students. Our main intention was that we selected one specific group that holds paramount importance for innovations driven by OGD (Lnenicka et al., 2022; OECD, 2016; Borgman, 2015; Golub & Lund, 2021). The study was contextualized in India with a sample of 530 currently-enrolled university undergraduate and postgraduate students of a leading private varsity. For our study, we realized a step-by-step approach to constructing and evaluating a model that enables an understanding of the nature of previously unexamined composite impact (direct, moderating, and indirect) of personality traits on behavioral intention to adopt and use OGD. Our empirical results indicated that the main drivers of the behavioral intentions to use OGD can be categorized into five groups as follows: (1) Trust (positive) and Performance Expectancy (positive); (2) Openness to Experience mediated by Performance Expectancy (positive), Effort Expectancy (positive), Social Influence (positive), Facilitating Conditions (positive), Information Quality (positive) and Trust (positive); (3) Conscientiousness mediated by System Quality (positive), Information Quality (positive), Data Quality (positive); (4) Agreeableness mediated by Voluntariness of Use (positive); (5) Emotionality mediated by System Quality (negative) and Information Quality (negative). The theoretical model was further tested according to personality traits moderating role. Our results allow us to suggest that the factors of Honesty–Humility and eXtraversion are able to demonstrate the ability only to "maintain", but not "strengthen" or "weaken" the relationships between Information Quality and Trust factors and users' Behavioral intention. It is valid in conditions when the rest of the personality traits directly affect OGD-related technology adoption factors.

From a *theoretical* perspective, the results complement the scientific literature on technology adoption and use by (1) testing and verifying the viability of applying the extended UTAUT model in an OGD context; (2) enriching the theory of technology acceptance and use OGD with HEXACO personality traits differences and exploring the types and strength of the relationship between these traits with Behavioral Intentions to use and adopt OGD by students of developing countries. Our research underscores the significant role personality traits play in shaping the behavioral intention toward students' adoption and usage of OGD. It is essential that this line of research continues to expand in various contexts, incorporating all OGD stakeholders. This broader involvement would enable a more comprehensive understanding of the subject. As for the non-significant relationships in the present study, it may be argued that students' personality traits have different implications across technologies' preferences, learning-goal orientations and achievement-motivations (Katrimpouza, 2019; DeLone & McLean, 2003), and, these determinants might be considered in further studies as well with respect to OGD adoption and usage. The study was undertaken in a developing country and this is an important *academic implication* wherein further research ought to be conducted in developed countries and/or a comparative assessment be made between the developed and developing countries with regard to the influence of personality traits on the OGD adoption and usage behaviors given the cultural differences among the users.

From a *methodological* perspective, we contribute by introducing an approach of incrementally building and evaluating a combined model that provides an understanding of the nature of the consolidated (moderating and indirect) type of effect of personality traits on behavioral intention to adopt and use OGD. Finally, the study contributes towards unraveling the *practical implications* of personality traits for technology adoption research in general and OGD research in specific. As such, there were convergent and divergent findings in terms of the role of personality traits at the individual level across OGD vis-à-vis other technologies thereby calling the need for furthering up this research contours in the domain of behavioral public administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tele.2023.102073.

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