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Long Paper

Adoption Conceptual Model for Intelligent Waste Management in Smart Cities: Theoretical Review

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Abstract

Purpose –Adoption of technologies in waste management in developing countries has largely lagged leading to poor waste collection and disposal exposing the city dwellers to health hazards and points of extortion. The delay has been occasioned by several technology adoption inhibitors. This paper, therefore, proposes am integration of three adoption models: diffusion of innovation (DoI), technology acceptance model (TAM) and technology readiness index (TRI) models towards enhancing understanding of the factors that may influence acceptance and use of smart waste management system in a smart city

Method – This paper critically reviewed the available literature on DoI, TAM, and TRI models and highlighted the challenges of applying each model and thereafter, proposed an integrated model based on the strength exhibited by each model.

Results –Despite the wide use of DoI, TAM, and TRI models, the models have weaknesses when applied independently for intelligent waste management. For instance: DoI focuses on innovation rather than information technology, does not support participatory adoption of technology, and lacks psychometrics characterization of users' behavioral intentions; TAM may not measure user's readiness and deals with perception to use technology rather than the actual use; TRI presupposes that users must be well equipped with the required infrastructure, skills, beliefs, and attitude to use technology. The integrated model may solve these weaknesses by drawing from the strength of each model while focusing on innovation (DoI), perceptions (TAM) and readiness (TRI)

Conclusion – The model may enhance the adoption of the waste management system by focusing on(i) the innovation covered byDoImodel and (ii) the intended users; characterized by both perceptions through the TAM model; and readiness provided by the TRI model.

Recommendations – The study recommends the actual application of the model to test the hypothesis adduced that integrating the models would enhance the adoption and use of intelligent systems for waste management in smart cities.

Practical Implications – *T*he proposed model could help city planners to formulate a good strategy mix for the intended use(rs) of an intelligent waste management system.

Keywords – Smart cities, intelligent systems, waste management, adoption, model

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INTRODUCTION

Smart cities

International Telecommunication Union (ITU) describes a smart sustainable city is an innovative city that uses ICTs and other means to improve quality of life, the efficiency of urban operation, services provision, and competitiveness while ensuring that it meets the needs of present and future generations concerning economic, social and environmental aspects (ITU, 2014). This means that smart cities gather and use real-time data analytics for prediction and planning for future growth, infrastructure development, and maintenance to meet the ever-changing demands of the citizens. Smart cities are characterized by integrated systems which facilitate smart mobility (transport systems), buildings (energy efficient) (Ernst & Young, 2015), healthcare, waste management (Hoornweg&Bhada-Tata, 2012), e-governance (Nielsen, 2017), economic activities, water resource management, and smart users. The integration promotes data generation processing, mining, and shared use for improved performance and optimal utilization of resources. By leveraging the use of digital technologies, smart cities can overcome the limitations of managing urban infrastructure and isolated developments (Economic and Social Council, 2016). Thus, the cities are meticulously planned to allow future expansions.

According to McKinsey &Company (2016), 70% of sustainable development goals will be realized through smart cities. This is because smart cities are progressive, resource-efficient, and provide high-quality services to the city dwellers. This has been achieved by creating synergies across systems to provide objectives and solutions to the dynamic environment of the cities. For instance: in Gujarat International Finance Tec-City in India, multiple utilities are co-located into a single data stream forming an integrated intelligent system that can be managed centrally (Economic and Social Council, 2016); In Barcelona, Spain, through the GrowSmarter Project the city installed fiber optics interconnecting major installations and services thus enabling open, efficient and user friendly services (European Commission, 2017); In Bristol, United Kingdom, the city implemented Replicate Project which deployed smart integrated energy, mobility and ICT solutions in a bid to curb carbon emission through efficient use of clean energy (European Commission, 2017); Similarly, in Cologne, Germany, the city is implementing smart solutions and integrated infrastructure to reduce carbon emission and thus become sustainable (European Commission, 2017). These are just some of the modern cities that have applied ICT solutions to enhance the quality of service provision to the citizens. Unlike in these modern cities, adoption of technology and success of smart cities in developing countries have generally lagged as a result of inadequate ICT infrastructure (inconsistent network connectivity), low ICT literacy levels, poor government policies supporting automation, resistance to change, lack of experienced professionals and insufficient funding (Vu & Hartley, 2018).

Smart cities have particularly exploded with the advent of cloud computing, open data, and the internet of things (IoT) which integrates data from smart objects and applies analytics tools to provide highly specialized data-driven decisions. According to Gartner (2017), IoT devices will increase from 8.4 billion in 2017 to 20.4 billion by 2020. In turn, this will push smart city devices to top 1 billion by 2025 (IHS Markit, 2016). To successfully implement a smart city, the following digital infrastructure is key: comprehensive and high-speed network, big data, IoT devices, sensors and platforms (Economic and Social Council, 2016); applications and tools with data analysis capabilities to run on the physical infrastructure; and user adoption characteristics and experiences for better decision and behavior change among city dwellers.

This paper critically reviewed the aspect of technology adoption as the key drivers of smart cities with specific regard to the adoption of intelligent waste management systems. This is because smart cities require users to adopt and actively use the resources of the technologies productively in their day to day life, service, and business. For example, the use of parking apps to guide users on available parking space, enhanced mobility using taxi apps, use of clean energy, and waste collection and disposal system. These services can only make sense when used by the intended users. The section below discusses the concept of waste collection and disposal as a key aspect of a smart city.

Waste Collection and Disposal

Waste generation is increasing at an alarming rate thus cities experience challenges in sorting, recycling, and disposing of waste especially solid waste (Wilson & Velis, 2014). In Norway, various municipalities are efficiently managing waste through increased recycling and incineration for the generation of energy to the extent of importing waste from other countries. However, in developing countries, most cities grapple with the problem of increased generation of waste arising from the ballooning population, poor disposal attitude, lack of disposal facilities, inability of the governments to enforce waste disposal laws and regulations, failure to prioritize waste management, insincerity among private sector waste operators and inadequate infrastructure (Becidan et al., 2015). In Nairobi City, 2475 tonne of waste is produced every day, but due to poor disposal strategy, the wastes have remained an eyesore in the city (Leah, 2018) due to poor monitoring, collection, transportation, processing, recycling, and disposal of the waste.

According to Otieno and Omwenga(2015), one of the key challenges in waste management is the inability to predict when the waste bins are full for disposal to appropriately schedule garbage collection trucks and thus reduce cases of waste spillage or misuse of resources whereby a truck is sent to collect waste when the bins are not full. Therefore, introducing smart waste management systems will leverage the use of IoT/sensors to send real-time data at the source to aid in the smart management l of waste. The system creates methods for proper handling of waste including enhanced efficiency in waste collection, categorization at the source, pick up, reuse, and recycling. Such systems are already being used in Santander, Spain (Urban Waste, 2017), and Sharjah, United Arab Emirates (NS Energy, 2020).

A typical smart waste management system uses sensors to measure the fill levels of waste collection bins. The measured data is transferred via cloud services to a central system or an onboard system connected to garbage trucks for processing and analysis (Pardini et al., 2020). The sensors can segregate waste by separating solid waste from liquid waste to ease transportation. Through analysis, trash collections are planned, and truck routes are optimized to reduce the cost associated with a waste collection when the bins are not yet full (Golubovic, 2018). The system can also employ a digital tracking and payment system which encourages users to correctly dispose of waste and receive payment in cash or kind.

According to McKinsey and Company (2018), smart cities can reduce the volume of solid waste per capita by 10–20% and 30-130 kg/person annual reduction in unrecycled solid waste thus delivering a cleaner and more sustainable environment.

Therefore, the need to implement an intelligent waste management system to enhance the city‘s capability to collect and dispose of waste especially in Nairobi city is long overdue. However, due to the inherent adoption challenges (such as resistance to change by users/stakeholders, endemic corruption, inadequate ICT infrastructure, and low ICT literacy levels (Leah, 2018), there is a need to apply an appropriate technology adoption framework for widespread acceptance and use of the system. This paper, therefore, reviews three technology adoption models namely diffusion of innovation, technology acceptance model, and technology readiness index, and proposes the integration of the three models to enhance understanding of the factors that may influence acceptance and use of smart waste management system as a critical aspect of a smart city.

TECHNOLOGY ADOPTION MODELS: REVIEW

Diffusion of Innovation (DoI) Model

DoImodel deals with the speed at which innovation is adopted by members of a social system and is measured by the number of users adopting innovation over some time (Rogers, 2003). DoI proposes the adoption of innovations based on either time, a channel of communication, innovation, or social systems (Sila, 2015). Dillon and Morris (1996) opined that technology or innovation spread at a rate that is proportionate to the level of integration with the existing beliefs, practices, norms, and culture of the society. The theory provides that the adoption of innovation is a decision of full use of innovation as the best course of action (Rogers, 2003). Considering the heterogeneity of the society, the level of acceptance varies based on adopters 'characteristics ranging from the earliest to the latest adopters.

Rogers (1983) categorizes members of social systems in the form of innovators (2.5%), early adopters (13.5%), early majorities (34%), late majorities (34%), and laggards (16%). Therefore, each member of society plays a critical role in the adoption of technology. The roles are affected by user-perceived adoption factors (Rogers, 1983) including complexity - which is the perceived effort to be put by users to use the technology; trialability- which is the initial phase of familiarization and experiencing the functionality of the system before deciding whether to adopt it or not; observability- whereby the system provides observable results; relative advantage- which is the perceived benefits that accrue to the users by using the system; perceived compatibility- which is the level of integration of the system with existing technologies and users way of life (Lundblad, 2003).

Several scholars have applied DoI to study technology acceptance and use. For instance, Zhang et al. (2015) applied DoI to understand the factors impacting patient acceptance and use of consumer e-health innovations, the study found out that majority of patients did not adopt the innovation due to insufficient communication, lack of value of the service, incompatibility of the new service and limitations of the characteristics of the patients; Xue(2017) applied DoI to characterize faculty attending professional development programs and found out that characterizing and leveraging the type of adopters and targeting the need of each adopter present in groups of participants can enhance the effectiveness of the program and increase adoption; and Sasaki (2018) applied DoI to educational accountability, the study showed that targeted aspects of curriculum policies were affected by all characteristics of DoI even though relative advantage and observability stood out as compared to the rest.

DoI can be applicable in determining the adoption of smart waste management system because:

i. It provides a tool for measuring how, why, and how fast innovation meets its intended goals.
ii. It would be important to determine the level of fit (integration) of the new intelligent waste management system to the existing beliefs, practices, norms, and culture of the society (city dwellers),
iii. It would be necessary to assess the new intelligent system complexity – in terms of perceived effort to be put by users to use the smart waste collection technology
iv. It should enable trialability by different types of users (intelligent system developers, its system administrators, support staff and the end-users),
v. Observability: The system should provide visible output e.g chart-based reports and alerts or even smell or taste-based reports for the various types of wastes
vi. relative advantage: the intelligent system should be advantageous to use as compared with the current manual waste detection and management system
vii. perceived compatibility: The system should be made to have both backward (enable the current manual system users an option to continue with the manual system) and forward compatibility with an automated intelligent system

Therefore, a system which is reliable, user friendly, provides observable results, allows for the performance of trials before full implementation and compatible with the practices/norms of the city dwellers tend to be trusted, and accepted for use by many users, unlike those systems which are likely to introduce a new social order.

The weakness of this theory is that it focuses much more on innovation rather than information technology. It does not also support the participatory adoption of technology. DoI is also less practical in predicting outcomes since it focuses more on system characteristics, organization attributes, and environmental aspects. The model, therefore, lacks psychometrics characterization of users' behavioral intentions such as perceived ease of use, perceived usefulness, and actual use which are an outgrowth of attitude and thus can influence user's ability to accept or reject the use of a system as proposed in TAM.

Technology Acceptance Model (TAM)

TAM has increasingly been applied in understanding technology adoption because the model outlines the psychometrics characterization of users behavioral intention to use technology (Davis, Bagozzi, &Warshaw, 1989) based on:

a) Perceived enjoyment: this is the degree under which users of the smart waste management system will perceive the use of the system as being pleasant or enjoyable.
b) Perceived ease of use: users of the system need not undergo extreme training or skills enrichment to interact with the waste management system. The system should be user friendly with an intuitive and interactive interface and support services.
c) Perceived usefulness: this is the extent to which the system transforms an input into the desired output. The smart waste management system should be effective and efficient in managing waste collection and disposal. This agrees with the DoI model
d) Attitude towards using the systems: perceived ease of use, enjoyment, and usefulness of the system would impact users ‘attitudes towards either adopting or rejecting the use of the smart waste management system.

Perceived ease of use and perceived usefulness are moderated by the user experience while working with the technology which in turn influences user‘s decision to accept or reject the technology. Asiri, Mohamud, Abu-Bakar, and Ayub (2012) in Alharbi and Steve (2014) confirmed that a positive attitude towards technology will likely motivate a user to utilize the technology. Other studies also found out that beliefs were important in determining the use of technology. Alharbi and Steve (2014) note that the use of technology could be predicted by the competency level which affects the utilization of the technology. Technology acceptance can also be influenced by organizational, technological, and social barriers, and demographical factors such as gender, computer self-efficacy, and levels of training.

Scholars have applied TAM in understanding and explaining user behavior in the adoption of technology. For instance: Kalina and Marina (2017) applied TAM to study online shopping adoption among youth in the Republic of Macedonia, the study found out that TAM served as a model of explanation of online shopping behavior by presenting the current situation; Lule, Omwansa, and Waema (2012) applied TAM in M-Banking adoption in Kenya and found out that TAM constructs significantly influenced the adoption of M-banking services thus the framework can be used as a guide when assessing the adoption of an M-banking service and can be used in any developing country since it was generic; Mugo, Njagi, Chamwei and Motanya (2017) applied TAM in predicting the acceptance and utilization of various technologies in teaching and learning places, the study found out that there were challenges of attitude towards technology, and educators must work hard to address attitudinal issues arising from learner, staff, management, and policymakers. Waleed et al. (2019) integrated DoI and TAM to evaluate students attitude towards MOOCs learning management system and recommended that system developers, designers and procurers should cautiously study the needs of students and confirm that the chosen system successfully meet their expectation since the MOOCs system features significantly affected user adoption; Lee (2009) combined TAM with theory of planned behavior to understand the perceived risks and benefits in adoption of internet banking and found out that perceived ease of use, perceived usefulness, attitude, subjective norm and perceived behavioral control are the important determinants of online banking adoption; Moon and Young-Gul (2001) introduced a newer variable "playfulness" in working with TAM to study acceptance of world wide web (www) and found out that perception of playfulness influenced users ' attitude towards using the www and should therefore be a consideration in designing future www systems by providing more concentration, curiosity and enjoyment.

Despite this wide use, TAM may not measure a user's readiness. For if we cannot measure then we can't know. Therefore, it is not possible to predict the behavior of semi-skilled users in the early stages of using a new system. The model also deals with perception to use technology rather than the actual use of technology. The model was also built to predict adoption in the work environment thus less applicable in an environment where users are autonomous like a city (Lin et al., 2007). It would be important to index users' readiness to accept, adopt the smart system as proposed by the TRI model.

Technology Readiness Index (TRI)

This model measures the user's readiness to accept new systems as influenced by contributor factors of optimism and innovativeness and inhibitor factors of discomfort and security of the system. The model describes how fast and at what rate users are adopting technologies. According to Parasuraman (2000), users have increasingly amassed technology products and services most of which did not provide any benefit to them. This is corroborated by the findings of Lin, Shih, and Sher (2007) study which concluded that the higher the technology readiness of customers, the higher the satisfaction and behavioral intentions generated when using self-service technologies. Parasuraman and Colby (2001) categorized customers into explorers, pioneers, skeptics, paranoids, and laggards whereby the explorers are the early adopters of innovation while the laggards are the late adopters. Explorers are driven by the technology contributing factors of optimism and innovativeness while the laggards are driven by the technology inhibiting factors of discomfort and insecurity. Pioneers tend to display similar beliefs as explorers, but also exhibit high discomfort and insecurity. Skeptics are dispassionate about technology, but also have few inhibitions; thus, they need to be convinced of the benefits of technology. Paranoids may find technology interesting, but they are also concerned about risks and exhibit high degrees of discomfort and insecurity (Massey, Khatri& Montoya-Weiss, 2007).

TRI has been used in many studies as an explanatory variable or as a moderator of a behavior, intention, or attitude. Pires, Costa Filho, and Cunha (2011) used TRI factors as differentiating elements between users and non-users of internet banking and found out that technology factors of optimism, security, and discomfort presented significant differences between users and non-users of internet banking; Nihat and Murat (2011) applied TRI to investigate technology acceptance in e-HRIM and found out that optimism and innovativeness positively influenced perceived usefulness and perceived ease of use but discomfort and insecurity did not have a positive effect on adoption of the system.

TRI provides alternative perspectives and views on the adoption of and satisfaction with the technologies by identifying: the techno-ready users who champion and can influence adoption; the users who are thrilled about adoption but must be reassured of the benefits of adoption; and users who require strong conviction and proof of concept before they adopt.

The challenge of TRI is that it focuses mainly on experiences and demographics and presupposes that for widespread adoption of technology users must be well equipped with the required infrastructure, skills, beliefs, and attitude.

Therefore, other than rating and diffusing smart waste management system users into early adopters, early majorities, late majorities, and laggards, there was a need to assess acceptance variation across and within these diffusion levels and index the techno-readiness among users. The next section depicts the integration of the three adoption models towards ensuring an understanding of the factors that would influence the adoption of a smart waste management system in a smart city.

PROPOSED CONCEPTUAL MODEL

Graphical representation of the proposed model

Implementing smart city technologies often require a robust, reliable, and affordable ICT infrastructure, an efficient ICT ecosystem as well as the right attitude for users to accept, adopt and use the technology. To gain a deeper understanding of the factors that would influence the adoption of an intelligent waste management system in a city in a developing country – for ease of planning- against the backdrop of inherent technology adoption inhibitors as discussed above, this paper proposes to integrate DoI, TAM, and TRI model to develop a model that will result in widespread actual-use of the waste management system (Figure 1). It is envisaged that the integrated model will inform the government and city planners on strategies of implementing a system that will be widely accepted by users for greater impact in waste management which has become a challenge to many cities.

TRI was chosen because it could easily be applied to determine whether a city dweller was a technology user or not, TAM was ideal because it can determine users perception about ease of use and usefulness of technology to develop the willingness to accept or reject the innovation, DoI was used because it provided positive behavioral intention to use a technology thus enhance the compatibility of technology with the current user activities and beliefs hence easy to use. Such an approach was initially proposed by Lin et al (2007) which proposed a combination of TAM and TRI and Waleed et al. (2019) which integrated DOI and TAM while in Walczuch, Lemminkb, and Streukensb(2007), technology readiness construct was associated directly with TAM‘s dimension of perceived of usefulness and perceived ease of usefulness.

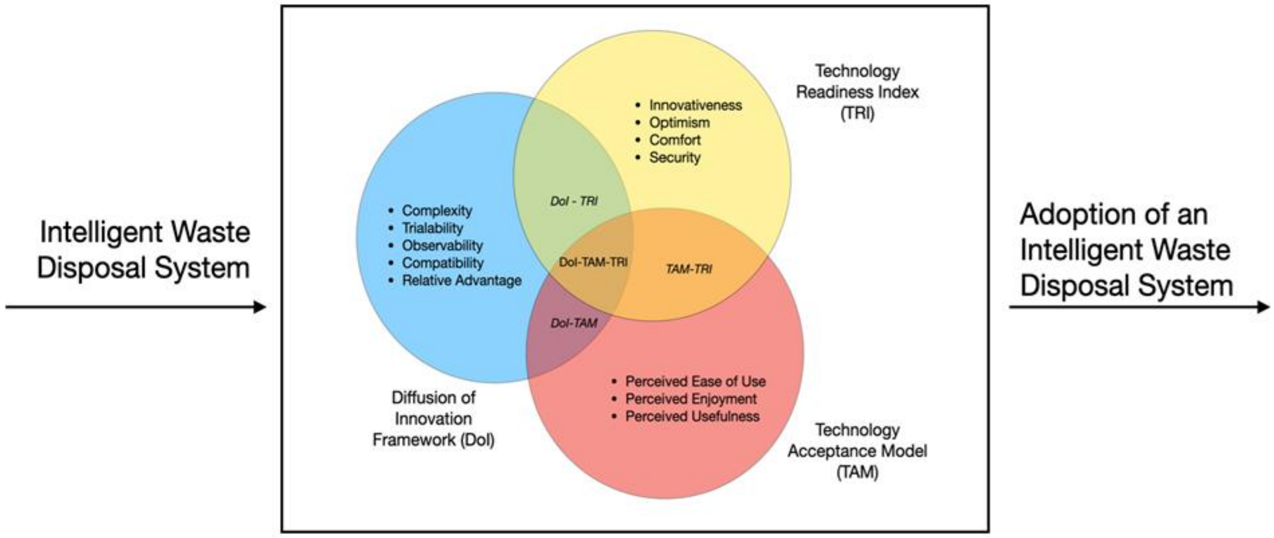

Figure 1. Proposed Integration of DoI, TAM and TRI model for the Adoption of an Intelligent Waste ManagementSystem (Author, 2020).

However, the combination of the two models would not adequately solve the adoption challenges. For instance:(i) whereas TRI antecedents may correlate to DoI constructs, their combination does not take into account the mediating factors such as psychometrics characterization of users' behavioral intentions, (ii)a study by Pires et al. (2011) found out that combining TRI and TAM led to only 3% increase in the intention to use technology, also a study by Godoe and Johansen (2012), found out that only optimism and innovativeness significantly affected perceived ease of use and perceived usefulness when TAM and TRIare combined, (iii) DOI variables of complexity and relative advantage are overlapping with TAM variables of perceived ease of use and perceived usefulness respectively (Carter &Bélanger, 2005) thus their combination may not provide a good prediction of adoption and use of technology. Therefore, the integration of the three models sought to solve the weaknesses of each model when applied independently or a combination of two models by focusing on innovation (DoI), perceptions (TAM), and readiness (TRI).

Discussion of the Model

Previous studies discussed herewith have not explicitly dealt with how the DoImodel relates to the behavioral intention to use a system as suggested in the TRI model. While it is worth exploring such a link, the proposed model hypothesizes that to maximize adoption for an intelligent waste management system that meets the DoI constructs of complexity, trialability, observability, compatibility, and relative advantage, both the intended users' readiness and perception has to be considered rather than just either of which.

Table 1. Table showing the factors exhibited by each group of techno-ready users and the corresponding index scale (metric), (Author, 2020)

Factors	Techno-Ready Users				
	Explorers	Pioneers	Skeptics	Paranoids	Laggards
Innovativeness	yes	yes	Yes	no	no
Optimism	yes	yes	No	yes	no
Discomfort	no	yes	Yes	yes	yes
Insecurity	no	yes	Yes	yes	yes
Index Level	**1**	**2**	**3**	**4**	**5**

As shown in Table 1 above, the readiness index is determined by the technology contributors of innovativeness and optimism, and inhibitors of comfort and security which enables the identification of techno-ready users who are likely to be the early adopters, and the explorers, pioneers, skeptics, paranoids, and the laggards who tend to be the late adopters. The index level 1 indicates the users who are extremely likely to adopt technology while 5 represent those extremely unlikely to adopt. Explorers exhibit both optimism and innovativeness. Pioneers tend to display similar beliefs as explorers, but also exhibit high discomfort and insecurity. Skeptics are dispassionate about technology but also have few inhibitions; thus, they need to be convinced of the benefits of technology. Paranoids may find technology interesting, but they are also concerned about risks and exhibit high degrees of discomfort and insecurity. And the laggards merely exhibit factors of discomfort and insecurity. In this model, it is hypothesized that the DoI constructs of compatibility are ideal in assessing the innovation in terms of backward and forward integration with existing or newer systems; observability assesses system provisioning of visible output for easier manipulation by users; while trialability allows users to try and test the functionalities of the system before full deployment.

Perception with regards to ease of use, enjoyment, and usefulness provides the framework for understanding the users' attitudes towards using the system. While perceived ease of use and perceived usefulness is likely to significantly influence the actual adoption/use of innovations as had been validated by studies in TAM (Kalina& Marina, 2017; Lule et al., 2012; Mugo et al. 2017; Waleed et al. 2019; Lee, 2009; Moon & Young-Gul 2001), the proposed model intended to create an understanding of the interconnectedness of the DoI, TAM and TRI models by drawing from the strength of each model while focusing on innovation (DoI), perceptions (TAM) and readiness (TRI)to help city planners appropriately formulate a good strategy mix for the intended users of an intelligent waste management system. A techno-ready user at index level 1 is extremely likely to adopt the innovation since they exhibit the ideal adoptive perception and behavior unlike at level 5. The researchers intend to further this study by testing the hypothesis through the actual implementation of the proposed model.

CONCLUSION

The models of DoI, TRI, and TAM, in this theoretical review, reveals to be complementary to each other. The TAM model addresses what it lacked in the DoImodel, which is the psychometric characterization of users' behavioral intention while the TRI model enables the measurement of user's readiness which is not covered in TAM.

Therefore, the integration of these three models covers the two key actors in the adoption of an intelligent waste management system: the innovation itself as may be focused by the DoImodel and the intended users; characterized by both perceptions through the TAM model; and readiness provided by the TRI model.

The knowledge gained from this proposed model of integration is deemed advantageous for city planners in crafting more appropriate strategies for the adoption of smart waste management system by the intended users; thus, enabling developing countries to experience the benefits of intelligent systems and consequently embrace further the concept of smart cities.

The study recommends the actual application of the model to test the hypothesis that integrating the models would enhance the adoption and use of intelligent waste management systems in smart cities.

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