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Factors affecting the acceptance of information systems supporting emergency operations centres

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ABSTRACT

Despite the recognition that information system acceptance is an important antecedent of effective emergency management, there has been comparatively very little research examining this aspect of technology acceptance. The current research responded to this gap in literature by adapting and integrating existing models of technology acceptance. This was done in order to examine how a range of technology acceptance factors could affect the acceptance of emergency operations centre information systems. Relationships between several of these factors were also examined. Questionnaire data from 383 end-users of four different emergency operations centre information systems were analysed using structural equation modelling. This analysis concluded that technology acceptance factors of performance expectancy, effort expectancy, social influence and information quality explained 65 percent of variance in symbolic adoption, which is a combination of mental acceptance and psychological attachment towards an information system. A number of moderating effects of age, gender, experience of use and domain experience were also identified. A mediating component, of performance expectancy, explained 49 percent of variance between facilitating conditions, information quality, effort expectancy, and resulting symbolic adoption. These findings highlight a need to re-focus technology acceptance research on both mediating and moderating effects and the importance of considering domain specific factors. Applied recommendations are also made, for successfully implementing relevant information systems.

1. Introduction

Information systems that support emergencies have the potential to save lives and minimize economic loss. As stated by Prasanna, Yang & King (2013), information is the most important resource in emergency management as it is the core input for decision making. Around the world, the importance of using information systems to support decision making of emergency operations centre personnel has been acknowledged since major disasters such as the 9/11 and the London 7/7 bombing (Prasanna, 2010).

Emergency operation centre information systems (EOCISs) are different from other information systems which are used in day-to-day office environments (Prasanna, 2010). EOCISs operate in extreme and stressful environments, where end-users not only need static information but also dynamic, real time updates. EOCISs are also characterized by infrequent use (Turoff, Chumer, Van de Walle, & Yao, 2004), which represents a further complication. They may sit relatively unused until an emergency, when they are picked back up by emergency managers and volunteers, performing roles which are very different to their day-to-day jobs.

EOC operators' information requirements remain complex, dynamic, and ad hoc. To cope effectively with natural or man-made hazard events like fire, flood, tsunami or terrorist attack and to avoid fatal catastrophes, it is essential to have appropriate information about the way these situations are developing. Emergency responders need to identify the situational context of an emergency, for example a large fire in a building, so that a range of key decisions can be made quickly and accurately (Jennex, 2007; Roth, Patterson, & Mumaw, 2002). Hence, it is important to develop information systems which provide crucial information rapidly to help make vital decisions accurately, from the onset of an emergency (Endsley, Bolte, & Jones, 2011; Jennex, 2007).

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1.1. The issue of end user acceptance

Despite substantial investments made to purchase and implement EOCISs, many of these systems have been struggling to gain the trust of end users (May, Mitchell, & Piper, 2014). Many systems appear to have faced rejections or replacements within a few years of implementation (Van de Walle, Turoff, & Hiltz, 2010). A seminal information system implementation model by Cooper and Zmud (1990) outlines how implementation of an information system cannot always be achieved in a single stage. Instead, it is a work in progress and implementation can be seen as an extended process, involving the six stages shown in Fig. 1: Initiation, Adoption, Adaption, Acceptance, Routinisation and Infusion.

End-users' use of a system does not necessarily mean that the system is fully implemented or accepted. Within the information system implementation model, this is not assumed to occur until the system reaches the highest-level of implementation: *infusion*, where end-users are fully satisfied with the system (Cooper & Zmud, 1990). Implementation of any type of information system therefore requires careful support and guidance, with responsive and focused improvements which will help achieve the infusion stage through progressively higher levels of end-user satisfaction. There is a growing body of research examining the determinants of information technology acceptance and utilization among end-users (Chau & Jen-Hwa Hu, 2002; Taylor & Todd, 1995). Such research enthusiasm has resulted in a number of theoretical models that attempt to explain the relationship between user attitudes, perceptions, beliefs, and eventual system use, including: the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980); the theory of planned behaviour (TPB) (Ajzen & Madden, 1986); the technology acceptance model (TAM) (Davis, 1986); and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003).

A large body of research informing the use and adaptions of the TRA, TPB, TAM and UTAUT models has included research into end-user acceptance of systems and technologies for: public services (for example, Moores, 2012), business management (for example, Zhou, Lu, & Wang, 2010) and organisational management (for example, Nah, Tan, & Teh, 2004). Other research literature has examined end-user acceptance of generic information systems such as Enterprise Resource Planning (ERP) (Ekanayake, Prasanna, & Kuruppu, 2012).

In terms of emergency response, notable studies have explored technologies for supporting frontline first responders (see for example: Manoj & Baker, 2007; Van de Walle & Turoff, 2007). Widely disseminated research by Turoff et al (2004) and Chen, Sharman, Rao, and Upadhyaya (2007) have introduced design guidelines, for information systems supporting crisis management. There has also been numerous studies into the design and development of a variety of emergency management information systems such as the knowledge management system used to support disaster planning and response (Dorasamy & Raman, 2011), emergency response system supporting firefighters (Prasanna, 2010); information management system for Hurricane Disasters - IMASH (Iakovou & Douligeris, 2001); information system to provide information for typhoon (Kitamato (2005) and PeopleFinder (Murphy & Jennex, 2006). As illustrated by these examples, most of the information systems research conducted in the emergency domain has focused on the design and development of technology based systems. There has still been comparatively little research into end users' acceptance of information systems in the emergency management domain. Haataja, Häkkinen, and Sullivan (2011) used a refined version of TAM to investigate the acceptance of emergency alerting systems in a university context. Wu (2009) used TAM driven mix method research to explore the acceptance of the use of SMS based alerting system among secondary school students. Lindsay, Jackson, and Cooke (2011) conducted a mixed-methods, longitudinal evaluation of the implementation of mobile data terminals within one of the UK police force branches to develop a revised TAM model, M-TAM. They conducted a second, qualitative study to validate the ability of M-TAM to explain the acceptance of police mobile data terminals (Lindsay, Jackson, & Cooke, 2014). There are also several notable technology acceptance studies conducted in other emergency related domains such as healthcare and telemedicine. Moores (2012) conducted an information technology acceptance study in the healthcare industry. This study proposed a revised model based on the TAM model. Similarly Lai, Huang, and Yang (2012) also adapted TAM to study the acceptance of a telehealthcare technology product. Sun, Wang, Guo, and Peng (2013) used a variant of UTAUT to explore the patience acceptance of mobile health technology. However, there is very little research evidence related to the acceptance of information system in the EOC environment.

Information system acceptance remains a crucial challenge for emergency management organizations that are either starting an implementation or are starting to use these systems for responding to actual incidents. There is therefore a significant need for research into technical, organizational and human factor aspects of EOCIS acceptance. Substantial research is needed to help address these related issues and ensure that EOICs are more widely trusted, accepted and thereby used for successful emergency management.

1.2. Technology acceptance models

Among various technology acceptance models, Agarwal and Prasad (1999) suggested that TAM had already become the technology acceptance model which was most widely used by information system researchers. Perhaps this is because TAM was the first technology acceptance model to consider a wide range of empirical support (see Amoako-Gyampah & Salam, 2004). As shown in Fig. 2 this model was first introduced by Davis (1986, 1989), as an adaptation of the theory of reasoned action (TRA).

Venkatesh et al. (2003) nonetheless outlined how information technology researchers were confronted with a multitude of models. Researchers were therefore bound to separate constructs from models or choose a particular model and ignore potentials for contributions between models. Venkatesh et al. (2003) outlined the need for synthesis in order to reach a more unified view of users' technology acceptance. They extended the traditional TAM, to help overcome a number of known limitations (see for example: Sun & Zhang, 2006; Brown, Massey, Montoya-Weiss, & Burkman, 2002) and provide an alternative model of technology acceptance called the UTAUT. This model is summarized in Fig. 3. According to Venkatesh et al. (2003), the UTAUT model can be considered both parsimonious and comprehensive because it has generally explained more variance in usage intentions than predecessor

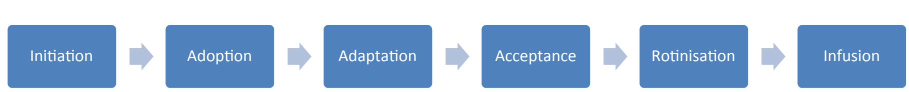

Fig. 1. Information system implementation model, adapted from Cooper and Zmud (1990).

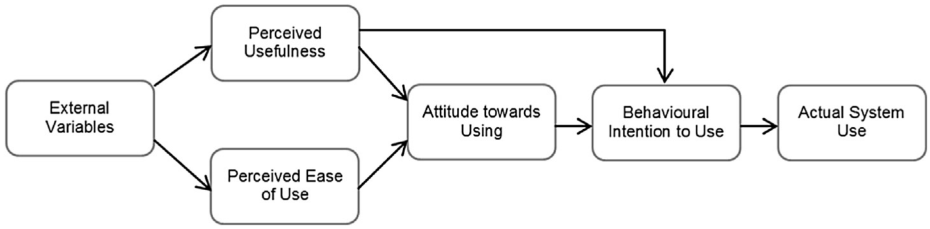

Fig. 2. TAM model, adapted from Davis (1986, 1989).

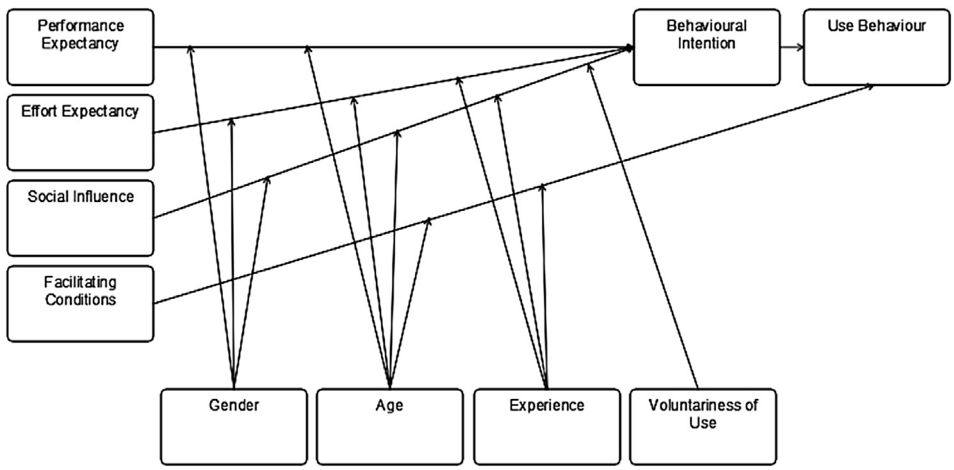

Fig. 3. Unified theory of acceptance and use of technology (UTAUT), adapted from Venkatesh et al. (2003).

models.

2. Theory

This section explains the theoretical foundation for dependent and independent variables in the current research model. It also explains the relationships between these variables. Having considered two of the most widely researched and empirically validated technology accepted models, the current research sets out to combine the strengths of both the TAM and UTAUT models. This has been done to develop a model which is as parsimonious as possible while providing insights into the acceptance and uptake of emergency management information systems.

2.1. Model variables

In addition to extracting suitable variables from the original TAM and UTAUT models the current research also considered the possibility of strengthening the proposed model by bringing variables from modified UTAUT and TAM models used in other closely related domains. As a result an additional independent variable *information quality*, drawn from a modified version of the TAM model is identified as suitable. Information quality has been identified as a crucial antecedent of technology acceptance in studies by Moores (2012) and Wixom and Todd (2005). The more recent of these studies, by Moores (2012) investigated the acceptance of a healthcare information system with similar features to an EOCIS and which operates in a comparably demanding domain. It therefore seems important to consider how information quality could be one of the key independent variables for the current adaptation of UTAUT.

Besides *information quality,* several other variables were also considered. This included variables such as *perceived trust* (Haataja et al., 2011); *compatibility* and *enabling factors* (Moores, 2012), *threat appraisals* (Sun et al., 2013); *risk-benefit assessment* (Wu, 2009) and *data quality* (Lindsay et al., 2011). Like *information quality,* all these variables were introduced to fine-tune the use of a pre-existing model. However when these variables are closely explored, it is evident that some of them are either a subset of the variables considered in the original UTAUT or in the TAM model. The rest are exclusive to a particular system or users being investigated. Therefore, apart from the inclusion of the variable *information quality,* none of the other variables are considered for the model proposed in this study. For example, the variable *compatibility* introduced by Moores (2012) can be considered as a subset of the variable *behavioural intention* which is one of the key variables of the UTAUT model while the variable *enabling factors* measures aspects very similar to one of the variables of UTAUT, *facilitating conditions*. Similarly, it seems that the root cause of the variable *perceived trust* introduced as a variation to the TAM model (Haataja et al., 2011) is addressed by the variable *performance expectancy* from the original UTAUT model. The *data quality* variable introduced from Lindsay et al. (2011) has not been accompanied by methods clearly explaining how to measure it and seems more of a subset of the *information quality* variable (Moores, 2012).

2.1.1. Behavioural intention and symbolic adoption in mandatory contexts

When exploring systems that are still going through implementation, it is common not to consider user behaviour as a dependent variable. Instead, actual use behaviour is replaced with a proxy of behavioural intention, being the intention of an end-user to make use of the new technology (Seymour, Makanya, & Berrangé, 2007). This approach is reinforced by Venkatesh et al. (2003) who analysed direct effects to conclude that all independent variables in the UTAUT model, except for facilitating conditions, influence use behaviour indirectly through behavioural intention. However studies by Rawstorne, Jayasuriya, and Caputi (2000) and by Brown et al. (2002) concluded that the behavioural intention construct may not be suitable for measuring acceptance in a mandatory environment. Apparently the results obtained can be self-contradicting and limited in terms of explaining end users' behaviours.

Defined by Nah et al. (2004) as an end-user's "mental acceptance" of a new system, *symbolic adoption* has been found to be a superior dependent variable in analyses of end-users' acceptance of systems (Karahanna, 1999; Nah et al., 2004; Rawstorne et al., 2000). In a more recent study of end-user acceptance of ERP systems, Ekanayake et al. (2012) defined symbolic adoption as a combination of mental acceptance and psychological attachment, with reference to Malhotra and Galletta (1999). Rawstorne et al. (2000) stated that end-users in a mandatory setting undergo symbolic adoption before actual system acceptance take place. They stated that end-users in a mandatory environment will demonstrate differences in symbolic adoption and that these differences can then be used to investigate and evaluate end-users' adoption of ERP systems.

As stated, the current research focuses on information systems which are yet to be fully implemented. The EOCIS's are still in a phase which Lu, Yao, and Yu (2005) refer to as *implementation*, characterized by partial adoption and use. According to Lu et al. (2005), intentions to adopt, alongside related factors, will even more strongly predict end-user uptake during this phase of implementation. For this reason and others outlined above, it was decided to operationalize end user's acceptance in terms of symbolic adoption, in place of behavioural intention, for the current research. It appeared that this approach would more accurately analyse the acceptance of EOCIS's which were still being fully implemented.

2.1.2. Performance expectancy

The *performance expectancy* component of the UTAUT model was originally based on the *perceived usefulness* (PU) component of TAM and defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p447). Empirical comparisons of eight models by Venkatesh et al. (2003) found that the performance expectancy component of each model was the strongest predictor of behavioural intention. This factor remained significant at all points of measurement in both voluntary and mandatory settings, consistent with previous model tests (Agarwal and Prasad, 1998). Performance expectancy therefore constituted a robust antecedent of technology acceptance, for analysis in the current research.

2.1.3. Effort expectancy

Effort expectancy has been defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p.450). This factor was derived by Venkatesh et al. (2003), from the perceived ease of use (PEOU) component of TAM. Venkatesh et al. (2003) found that effort expectancy was strongly and significantly related to end-users' intentions to use an information system.

2.1.4. Social influence

Social influence has been defined by Venkatesh et al. (2003) as how strongly an end user perceives that others believe that he or she should use the new system. Studies by Kraut, Rice, Cool, and Fish (1998), Rice, Grant, Schmitz, and Torobin (1990), and Yuan, Fulk, and Shumate (2005) have found that the attitudes and behaviours of other individuals in a user's social and work circles significantly impact that user's use of technology. Institutional and social influence may be particularly relevant when new technologies are implemented within an organization because individuals experience ambiguity and uncertainty about the value of those technologies for their work (Weick, 1990). It follows that colleagues' beliefs about the new technologies may help assuage that ambiguity and uncertainty.

2.1.5. Facilitating conditions

Facilitating conditions are "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453). This component of UTAUT is made up of three factors: training and support; shared belief in the system; and project communication. Research into facilitating conditions by Seymour et al. (2007) used symbolic adoption as the sole dependent variable. Their interpretation of the UTAUT model included three factors representing facilitating conditions: training, belief in the system and project communication.

2.1.6. Information quality

Moores (2012) defined *information quality* as a combination of end-user's perceptions of accuracy, content, format, and timeliness. This construct is used to gauge whether a system is free of errors, whether it provides the information needed for the user to complete their work at the time they need it, and whether information is provided in a format which is easy to read. Widely cited research by Wixom and Todd (2005), into user satisfaction and the acceptance of information systems, found that information quality formed a unitary factor combining end-user perceptions of accuracy, precision, reliability and currency.

2.2. A combined model of EOCIS acceptance

In contrast to the traditional UTAUT model, the current study proposes a model which integrates features of both the UTAUT and TAM models. Having considered the TAM and UTAUT models alongside subsequent adaptations, the current research assumes that symbolic adoption depends on antecedents of performance expectancy, facilitating conditions, ease of use, information quality and social influence. However core TAM components of perceived usefulness and perceived ease of use have been replaced with performance expectancy and effort expectancy from the UTAUT model, to give a broader representation of user behaviour.

Perceived usefulness acts as a core mediator between behavioural intention and all antecedent components in the TAM. Since the introduction of the UTAUT model, most technology acceptance research has simply neglected this, or any other, potentially mediating factor. As outlined by Zhou et al. (2010), the UTAUT effectively replaced perceived usefulness with performance expectancy. Hence, in an effort to examine another potentially mediating effect, performance expectancy is treated as a mediating variable for the current research. This includes an additional mediating role, between facilitating conditions and behavioural intention. This additional meditating affect is predicted with reference to the extended, UTAUT2 model by Venketesh, Thong and Xu (2012), who concluded that end-users are more likely to intend using a technology when facilitating conditions such as training and system support are more freely available.

The original UTAUT model, by Venketash et al. (2003), assumed that facilitating conditions were insignificant amongst high levels of both performance expectancy and effort expectancy. Venkatesh et al. (2003) assumed that organizational settings providing facilitating conditions such as training and support would make these conditions freely and evenly available. The current research contradicts this aspect of the original UTAUT for the purpose of studying information systems being implemented across different physical locations under different organizational settings. Perceptions of facilitating conditions have changed drastically since the UTAUT model was first developed in 2003. There have been particular changes in training, amongst other facilitating conditions. As stated by Marginson (1997), many organisations have long since started to view training as a commodity, rather than an institutional obligation. It is likely that many contemporary organizations have since viewed training as a major cost, amongst relatively scarce support for systems. This commodity-based approach to training is assumed to lead to even more widely varying facilitating conditions, under varying financial constraints. Furthermore, end-users of a system in different locations may receive invariant facilitation due to their distance from headquarters, training centres and other training providers. A similar argument was made by Aggelidis and Chatzoglou (2009), and Jairak, Praneetpolgrang, and Mekhabunchakij (2009) who found a significant, direct relationship between facilitating conditions and intention to use of technology.

Having considered the factors outlined above, the current research proposed the following hypotheses:

1. that performance expectancy (PE) would mediate a positive effect of facilitating conditions (FC) on symbolic adoption (SA);
2. that performance expectancy (PE) would mediate a positive effect of information quality (IQ) on symbolic adoption;
3. that performance expectancy (PE) would mediate a positive effect of effort expectancy (EE) on symbolic adoption (SA); and
4. that performance expectancy (PE) would mediate a positive effect of social influence (SI) on symbolic adoption (SA).

Venkatesh and Morris (2000), Venkatesh et al. (2003, 2012) and Yi,Wu, and Tung (2006) outlined how gender influences the use of any information system in both mandatory and voluntary settings. Likewise, research by Venkatesh et al. (2003, 2012) identified that age can affect technology acceptance dynamics. The current research therefore examines the influences of demographic moderators age and gender on the relationships between all the exogenous and endogenous variables, including the dependent variable of symbolic adoption and the mediator, performance expectancy. Venkatesh and Davis (2000), and Xia and Lee (2000) observed that perceptions and adoption intentions increased substantially alongside end-users' direct-use experience.

The current research therefore also examined the role of end-user experience as a moderator, in two specific forms: 1. Experience of using the system; and 2. Previous EOCIS experience. The current research also explored the overall influence of emergency management experience, to identify any potentially moderating influence from this essentially demographic variable. These additional moderating effects are proposed alongside the main hypotheses, to form the current research model, detailed in Fig. 4.

3. Material and methods

The current study was focused on survey responses from the end-users of four popular EOCIS software packages: EMIS; Health EMIS; Veoci; and WebEOC. All four systems were being used at multiple physical locations at the time. Respondents using EMIS and Health EMIS were from local and national level EOCs in New Zealand whereas respondents using Veoci were from EOCs attached to the state level EOCs in USA. Respondents using WebEOC were from Australia and attached to regional EOCs. Regardless of the system being used, survey respondents included personnel with seven different EOC roles namely: control, intelligence, planning, operations, logistics, welfare, and public information management, or a position related to these main roles. None of the systems had been in implementation for more than three years but all had been used for responding to emergency events. Discussions with some of the end-users, developers and the owners of these four systems suggested that all the systems were still progressing between initiation and acceptance stages of their implementation.

Prior to conducting any data collection, this study underwent an ethical approval process concerning participation from human subjects. All participants were provided with an information sheet detailing their rights along with other ethical considerations. In addition, close communication was maintained with the software companies and participant organizations involved throughout the study. An anonymous online questionnaire survey was prepared using the Qualtrics Online Questionnaire Builder. It consisted of: 1. an invitation letter; 2. demographic questions; and 3. a series of five point Likert scale questions. The Likert scale questions were drawn from well-established, concise and psychometrically robust items from previous technology acceptance studies by Venkatesh et al. (2003), Seymour et al. (2007) and Moores (2012). The wording of these items was slightly adapted to match the current research contexts. The survey was piloted by several end-users who provided feedback for improvements to the questionnaire items and the overall questionnaire format. Following minor amendments, these end-users were satisfied that the questionnaire was both readable and straight-forward to complete. Items comprising the final version of the questionnaire are summarised in Table 1.

Questionnaires were then circulated among EMIS and Health EMIS end-user respondents by a senior manager who had been tasked with coordinating system implementation. The survey was also promoted via an internal news bulletin with an introduction and internet hyperlink to the survey. Software vendors of Veoci and WebEOC circulated the survey to their own end-users via email. Discussions with main contacts for survey distribution to EMIS, Health EMIS, Veoci and WebEOC end-users suggested that the research invitation was sent to approximately 3500 end-users. 480 end-users submitted responses to the online questionnaire, giving an estimated response rate of 13.71 percent. However it cannot be assumed that all invitees actually read the invitation email, making it impossible to calculate the actual response rate. The response rate was therefore likely to be higher than the current estimate, given that many emails were delivered to the in-boxes of personnel with pressing administrative workloads.

Missing values, outliers, and normality were assessed, to help ensure the quality of survey data as a whole. Of those who responded, 57 responses were either substantially incomplete or were unusable due to important missing values or obviously disinterested responses. Data was further limited to end-users with at least three months of system experience. This excluded a further 40 responses, on the assumption that end-users who had just started using the system would not have been able to answer all of the questions in a meaningful way. Ordinal data produced by five point Likert scales used in the questionnaire did not permit extreme value statistical outliers which may have required further filtering. A final total of 383 responses were filtered for data analysis, meaning that 79.8 percent of all collected data was retained. Table 2 outlines the diversity of this filtered sample, by participants' demographic characteristics.

4. Results

Data analysis consisted of four main stages. First, an exploratory factor analysis was completed using Statistical Package for the Social Sciences (SPSS) software, to ensure that model components met initial requirements for structural equation modelling. This was followed by a confirmatory factor analysis using AMOS

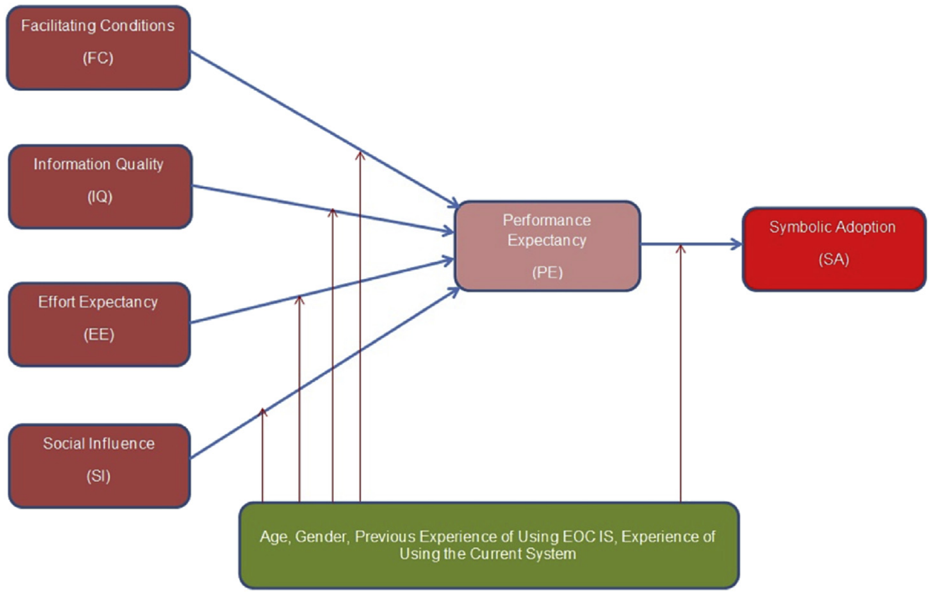

Fig. 4. Research model proposed for factors affecting end-user's acceptance of EOCIS.

Table 1
Questionnaire composition.

End-user perception	Number of questions	Notation	Literature sources
Performance Expectancy (PE)	12	PE1-PE12	Venkatesh et al. (2003)
Effort Expectancy (EE)	07	EE1-EE7	Venkatesh et al. (2003)
Facilitating Conditions (FC)	12	FC1-FC12	Venkatesh et al. (2003); Seymour et al. (2007)
Social Influence (SI)	06	SI1-SI6	Venkatesh et al. (2003)
Information Quality (IQ)	10	IQ1-IQ10	Moores (2012)
Symbolic Adoption (SA)	06	SA1-SA6	Seymour et al. (2007); Ekanayake et al. (2012)

Table 2
Sample demographics.

N = 383	Min	Max	Mean	St. Dev.
Age	20 yrs	70 yrs	43 yrs	1.103
Experience of Using the System	3 mths	3 yrs	1.835 yrs	0.806
Previous EOCIS Experience	3 mths	9.75 yrs	3.490 yrs	1.867
Emergency Management Experience	9 mths	37 yrs	4.951 yrs	5.800
Gender	66.3% Males, 33.7% Females			

Software. These first two steps enabled validation of the reflective measurement model. The third stage involved testing of the structural model in AMOS software by creating a composite variable for each model factor. This third set of tests used latent variable scores with regression imputation. This approach created one variable per factor and greatly simplified testing of the structural model. According to Gaskin and Godfrey (2014), it is a common approach to testing particularly complex models. The effect of mediation was tested using an approach from Baron and Kenny (1986) which was complemented by a bootstrapped analysis of indirect effects with 500 resamples. The fourth and final stage tested the overall structural model with all moderating factors, using an analysis of Chi-square differences from Yuan and Bentler (2004).

4.1. Measurement model

The final set of data was used to conduct exploratory then confirmatory factor analyses. These analyses used Maximum Likelihood and Promax rotations to establish the reliability and validity of the research model constructs, in terms of patterns in questionnaire responses. As shown in Table 3, item loadings for 23 questions had a Cronbach's alpha of more than 0.400, meeting the threshold from Hair, Black, Babin, and Anderson (2010) for sample sizes greater than 200. All constructs were also considered reliable at a generic alpha threshold of 0.700, from Fornell and Larcker (1981). A six factor model produced through exploratory factor analysis explained a total 76 percent of variance. Confirmatory factor analysis was then used to confirm this factor structure, alongside additional measures of validity and reliability.

According to Kline et al. (2011), an average variance extracted (AVE) greater than 0.500 establishes the convergent validity of factor variables. As shown in Table 4, all six factors met this criteria. According to Hair et al. (2010), composite reliability (CR) values in excess of 0.700 demonstrate reliability. All factors also met this criteria, as shown in Table 4. In addition, all factors satisfied a generic criterion for discriminant validity, where the square root of AVE for each factors' variables was greater than correlations between factors, as shown in Table 4.

Table 5 presents goodness of fit statistics for the six factor model. As detailed, these values met threshold values recommended by Hu and Bentler (1999) together with more recent recommendations from Hair et al. (2010). The model therefore did not require any further adjustments, to obtain an adequate goodness of fit.

Table 3
Pattern matrix.

	Factor						Corresponding questions
	1	2	3	4	5	6	
Cronbach's Alpha	.95	.91	.88	.89	.90	.96	
PE_1	.86						The system enables me to accomplish work tasks more quickly.
PE_3	.91						Using the system improves my efficiency.
PE_4	.91						Using the system increases my productivity.
PE_5	.92						Using the system positively affects the performance of my job.
PE_6	.74						Using the system increases the quality of my work.
PE_7	.83						Using the system increases how much work I produce for the same amount of effort.
EE_3				.80			Using the system takes too much time from my normal duties.
EE_4				1			Working with the system is so complicated, that it is difficult to understand what is going on in the system.
EE_5				.82			It takes too long to learn how to use the system to make it worth the effort.
FC_1			.57				My level of understanding was substantially improved after going through an system training program.
FC_6			.83				I was well informed of the system implementation in person, through presentations and through written media.
FC_7			.82				A specific person (or group) is available to assist me with operational difficulties of using the system.
FC_8			.88				Overall, I have been given adequate support for using the system.
SI_1						.87	Superiors in my organization who influence my work behaviour think that I should use the system for my work.
SI_2						.85	People who are important to me think that I should use the system for my work.
SI_3						.80	My supervisor is very supportive of using the system for my job.
IQ_1					.84		The system provides reports which address my needs.
IQ_2					.93		The system provides sufficient information.
IQ_3					.82		The content of information provided by the system meets my needs.
SA_1		.92					I want to see the system fully utilized and deployed.
SA_2		1					I am excited about using the system in my workplace.
SA_3		.92					I am enthusiastic about using the system.
SA_6		.74					I feel a sense of personal ownership about using the system.

Table 4
Construct correlation matrix.

Construct	CR	AVE*	1	2	3	4	5	6
1.Performance Expectancy (PE)	0.92	0.66	**0.81**					
2. Effort Expectancy (EE)	0.96	0.85	0.65	**0.92**				
3. Facilitating Conditions (FC)	0.95	0.82	0.53	0.65	**0.90**			
4. Social Influence (SI)	0.91	0.77	0.50	0.54	0.48	**0.88**		
5. Information Quality (IQ)	0.85	0.65	0.57	0.55	0.52	0.41	**0.81**	
6. Symbolic Adoption (SA)	0.91	0.79	0.41	0.55	0.56	0.50	0.40	**0.89**

Note: Square root of the AVE on the diagonal.

Table 5
Goodness of fit for the measurement model.

Criteria	Reported value	Recommended threshold
CMIN/df	2.14	<3 and >1
CFI	0.97	>0.95 great; >0.90 traditional
RMSEA	0.055	<0.05 good; 0.05–0.10 moderate
PCLOSE	0.132	>0.05
SRMR	0.055	<0.09
GFI	.910	

4.2. *Structural models*

Statistical analyses of the structural model tested the model's ability to explain relationships between the dependent and independent variables. Corresponding R^2 values, representing the amount of variance explained by each independent variable, were also tested. This combination of loading and significance analysis indicated how well the data supported the current research hypotheses. As shown in Fig. 5, the conceptual research model was analysed with the mediator and then without the mediator. The latter analysis is shown in Fig. 6 and both used an approach to structural equation modelling from Baron and Kenny (1986).

Despite being made up of complex composite variables, both the mediated and unmediated models achieved excellent goodness of fit, as shown in Table 6.

As shown in Figs. 5 and 6, endogenous variables explained a high proportion of total variance in both the mediated and unmediated models. For the unmediated model, R^2 was 52 percent for symbolic adoption (SA). For the mediated model, R^2 for symbolic adoption was 65 percent, while R^2 for performance expectancy (PE) was 49 percent. Total variance explained in symbolic adoption decreased by about 13 percent when performance expectancy was excluded as a mediator.

As shown in Table 7, the direct effects of exogenous independent variables facilitating conditions (FC), effort expectancy (EE) and information quality (IQ) on symbolic adoption (SA) were statistically significant, both with and without mediators. Bootstrapped indirect effects were statistically significant.

This clearly indicates partial mediation via performance expectancy between: facilitating conditions and symbolic adoption; effort expectancy and symbolic adoption; and information quality and symbolic adoption. However there was no significant mediation effect to be seen in the relationship between social influence and symbolic adoption. As shown in table it is clearly evident that there is no substantial difference between the direct effects of social influence on symbolic adoption with and without the mediator performance expectancy. Instead, a direct unmediated positive relationship was identified between social influence and symbolic adoption with a standardised regression weight of 0.170 which was significant at the $p < .001$ level.

4.3. *Moderating effects*

Multi-sample (sub-group) tests were carried out to explore the

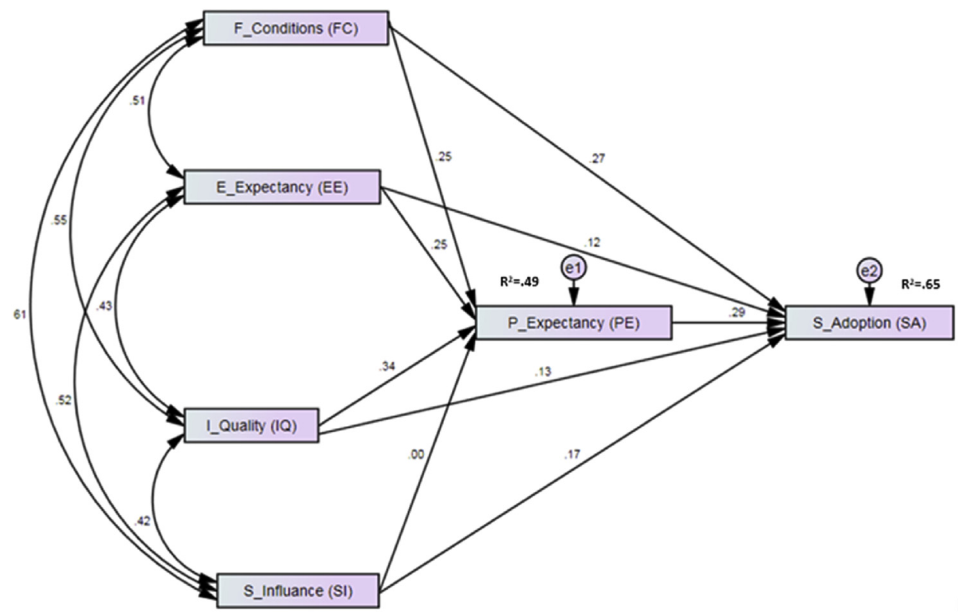

Fig. 5. Structural model with mediator.

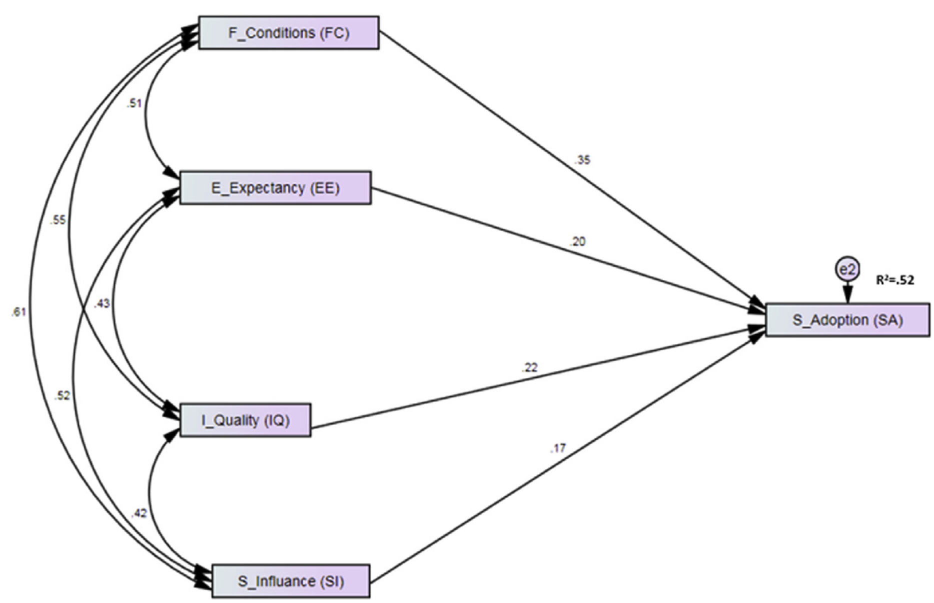

Fig. 6. Structural model without mediator.

Table 6
Model fit for mediated and unmediated structural model.

Criteria	Unmediated structural model	Mediated structural model
CMIN/df	1.626	1.983
CFI	0.998	0.997
RMSEA	0.040	0.051
PCLOSE	0.559	0.417
SRMR	0.036	0.036
GFI	0.996	0.996

influence of five moderating variables on the model as a whole: 1. experience of using the system; 2. gender; 3. age; 4. previous EOCIS experience; and 5. emergency management experience. This multi-group analysis verified whether significant differences existed between levels of each moderator based on the strength of their path coefficients. Each moderator was analysed by constraining each path coefficient to remain equal across levels. The resulting model fit was compared with the unconstrained model, using the Chi-square difference test to reflect an analytical procedure from Holmbeck (1997).

Experience of using the system was normally distributed between 0.25 and 3 years with a mean value of 1.83 years and mode of 2.00 years. To examine the influence of experience of using the system, data was divided into two groups: less than and equal to or greater than 1.5 years of experience. Findings of the Chi-square difference test of these low and high experience groups are reported in Table 8. Relationships between effort expectancy and performance expectancy and between effort expectancy and

Table 7
Mediator effects.

Path	Direct without mediator	Direct with mediator	Indirect effect	Conclusion
FC->PE->SA	.346***	.273***	0.072** (.002)	Partial
EE->PE->SA	.196***	.122**	0.073**(.004)	Partial
IQ->PE->SA	.224***	.126**	0.097**(.005)	Partial
SI->PE->SA	.169***	.170***	−0.001(ns .888)	No mediation

***p < 0.001, **p < 0.01,*p < 0.05; (ns) = not significant.

Table 8
Moderation due to experience of using the system.

Constrained Paths	Low use estimate	High use estimate	Chi-square constrained	Chi-square difference
PE<—EE	0.364	0.193	44.662	4.341**
PE<—IQ	0.448	0.272	43.09	2.769*
PE<—SI	0.056	0.052	(ns path)	
PE<—FC	0.036	0.342	47.753	7.432***
SA<—FC	0.212	0.399	44.386	4.065**
SA<—EE	0.185	−0.002	46.375	6.054**
SA<—IQ	0.156	0.112	40.599	0.278(ns)
SA<—SI	0.16	0.053	42.207	1.886(ns)
SA<—PE	0.435	0.277	43.622	3.301*

Note: ***p<0.01, **p<0.05,*p<0.10.

symbolic adoption were significantly stronger when end-users had low experience of using the system. A similar relationship was observed between social influence and performance expectancy. However relationships between facilitating conditions and performance expectancy and between facilitating conditions and symbolic adoption were much stronger when end-users had high experience of using the system.

The data was also analysed by male and female genders, as shown in Table 9. Relationships between facilitating conditions and symbolic adoption and between information quality and symbolic adoption were significantly stronger for males. The relationship between performance expectancy and symbolic adoption was significantly stronger for females.

Participant ages had been divided into five categories in the electronic survey: 21–30; 31–40; 41–50; 51–60; and 61–70. 39.4 percent of end-users were over 50 years so data was then grouped into two categories; younger (≤50 year), and older (>51 years). The findings of a Chi-square difference test for these two age groups are reported in Table 10.

The following relationships were significantly stronger for older end-users: information quality and performance expectancy; facilitating conditions and performance expectancy; and facilitating conditions and symbolic adoption. By contrast, there was a significantly stronger relationship for information quality and symbolic adoption and between social influence and symbolic adoption amongst younger end-users.

A descriptive analysis of previous EOCIS experience showed that nearly 65 percent of participants had less than three years of experience of using some form of EOCIS system. 31.6 percent of users had three years of experience. Another 20 percent of participants had three to four years of experience and the rest had more than four years of experience, with maximum of 9.75 years. Previous EOCIS experience data was therefore grouped into two categories: Low previous EOCIS experience (≤3 years) and High previous EOCIS experience (>3 years).

Table 11 shows the results of a Chi-square difference test for low and high experience groups. The relationship between facilitating conditions and performance expectancy was significantly stronger for users with more than three years of previous EOCIS experience. The relationship between effort expectancy and symbolic adoption had a statistically significantly stronger relationship amongst users with three or less years of experience.

A descriptive analysis of emergency management experience showed that nearly 56 percent of participants had less than years of experience in emergency management while 24 percent of participants had three years of experience. Another 22 percent of participants had between three and four years of experience and the remainder had more than four years of experience, with a maximum of 37.17 years of emergency management experience. Data was therefore grouped into two categories: low emergency management experience (≤3 years) and high emergency management experience (>3 years). The findings of a Chi-square difference test for low and high emergency management experience are reported in Table 12. The relationship between facilitating conditions and symbolic adoption was significantly stronger for participants with more than 3 years of emergency management experience. Relationships between effort expectancy and symbolic adoption and between social influence and symbolic adoption were

Table 9
Moderation due to gender.

Constrained Paths	Male estimate	Female estimate	Chi-square constrained	Chi-square difference
PE<—EE	0.294	0.285	10.362	0.180(ns)
PE<—IQ	0.339	0.376	10.480	0.298(ns)
PE<—SI	−0.010	0.125		(ns path)
PE<—FC	0.275	0.020	12.175	1.993(ns)
SA<—FC	0.338	0.108	14.243	4.061**
SA<—EE	0.063	0.168	11.755	1.573(ns)
SA<—IQ	0.213	0.029	14.832	4.650**
SA<—SI	0.160	0.083	10.981	0.799(ns)
SA<—PE	0.271	0.436	13.990	3.808*

Note: ***p<0.01, **p<0.05,*p<0.10.

Table 10
Moderation due to age.

Constrained Paths	Younger estimate	Older estimate	Chi-square constrained	Chi-square difference
PE<—EE	0.336	0.231	19.15	2.328(ns)
PE<—IQ	0.245	0.478	23.015	6.193**
PE<—SI	0.088	−0.030	(ns path)	
PE<—FC	0.113	0.380	21.458	4.636**
SA<—FC	0.077	0.523	38.923	22.101***
SA<—EE	0.176	0.054	19.228	2.406(ns)
SA<—IQ	0.249	−0.057	30.209	13.387***
SA<—SI	0.221	−0.039	25.976	9.154***
SA<—PE	0.284	0.390	18.301	1.479(ns)

Note: ***p<0.01, **p<0.05,*p<0.10.

Table 11
Moderation due to previous EOCIS use experience.

Constrained Paths	Low use estimate	High use estimate	Chi-square constrained	Chi-square difference
PE<—EE	0.293	0.215	19.717	1.048(ns)
PE<—IQ	0.375	0.348	18.767	0.098(ns)
PE<—SI	0.048	−0.008	(ns path)	
PE<—FC	0.149	0.360	21.806	3.137*
SA<—FC	0.277	0.311	18.804	0.135(ns)
SA<—EE	0.144	0.004	22.109	3.440*
SA<—IQ	0.116	0.116	18.672	0.003(ns)
SA<—SI	0.156	0.067	19.715	1.046(ns)
SA<—PE	0.319	0.334	18.702	0.033(ns)

Note: ***p<0.01, **p<0.05,*p<0.10.

Table 12
Moderation due to emergency management experience.

Constrained Paths	Low estimate	High estimate	Chi-square constrained	Chi-square difference
PE<—EE	0.301	0.216	18.195	1.423(ns)
PE<—IQ	0.312	0.407	17.920	1.148(ns)
PE<—SI	0.062	−0.005	(ns path)	
PE<—FC	0.176	0.307	17.675	0.903(ns)
SA<—FC	0.222	0.386	20.094	3.322*
SA<—EE	0.188	−0.037	25.567	8.795***
SA<—IQ	0.116	0.136	16.844	0.072(ns)
SA<—SI	0.189	0.022	20.589	3.817*
SA<—PE	0.316	0.334	16.822	0.050(ns)

Note: ***p<0.01, **p<0.05,*p<0.10.

significantly stronger for participants in the low emergency management experience group.

5. Discussion

An iteration of the UTAUT model was used to show that end-user's expectations of performance using a system can mediate a positive relationship between antecedent variables and symbolic adoption of EOCISs. Hypotheses one to three predicted effects mediated by performance expectancy from facilitating conditions, effort expectancy and information quality, on the symbolic adoption of EOCISs.

The mediated and significantly positive relationship identified between facilitating conditions and symbolic adoption is relatively novel for technology acceptance research. This finding contradicts a key assumption of the original UTAUT model (Venkatesh et al., 2003) and several subsequent iterations, which have not identified any significant relationship between facilitating conditions and variables related to behavioural intention. The original Venkatesh et al. (2003) model went so far as to reject a relationship between facilitating conditions and behavioural intention to use in generic organisational settings. The current research therefore highlights a new potential to examine significant relationships between facilitating conditions and intentions to use information systems. Early research precedents may have led to devaluing this potential in recent technology acceptance research. It may be time to address this neglect, beyond the scope of EOCIS acceptance in particular.

Performance expectancy has been generally disregarded as a mediator by previous UTAUT research outside of emergency management contexts. Examples include: Zhou et al. (2010); Tan (2013); and Aggelidis and Chatzoglou (2009). Most previous studies have neglected the potential mediating effect of performance expectancy predicted in the TAM model. By contrast, Aggelidis and Chatzoglou (2009) identified a mediating effect for performance expectancy, reflecting a factor structure which is similar to the current research. Aggelidis and Chatzoglou (2009) conducted their research in a hospital context, using systems for supporting emergency management operations domain. The current research therefore makes a noteworthy further contribution to technology acceptance literature, by identifying such a significant mediation effect, across a range of EOCIS systems and contexts. Although specific to the emergency management context, the strength of current findings suggest that performance expectancy could mediate the acceptance of a range of information systems.

Although performance expectancy mediated effects from all other antecedent factors, it did not mediate the positive relationship between perceptions of social influence and the symbolic adoption of EOCISs. Instead, it appears that social influence maintained a direct, positive impact on symbolic adoption, with no relationship between social influence and performance expectancy. This finding contradicted hypothesis four, leading to a fairly intuitive implication: that a relatively indirect effect of social influence did not affect individual's personal beliefs about being able to effectively use the EOCISs.

The current research took an explorative approach to the moderating effects of gender, age, experience of using the system, previous EOCIS experience, and emergency management work experience. It was observed that experience of using the EOCIS system in question would weaken the relationship between effort expectancy and performance expectancy. By contrast, it was observed that previous experience of using EOCISs in general would have no significant moderating impact on this relationship.

High experience of using the system and of using EOCISs in general negatively moderated the direct relationship between effort expectancy and symbolic adoption. Emergency Management experience also weakened this direct relationship. Venkatesh et al. (2003) had observed similar moderating effects. They found that high user experience lessened the relationship between effort expectancy and behavioural intention. However the observed lack of moderation effects from age and gender differ from initial UTAUT research by Venkatesh et al. (2003). They observed that the relationship between effort expectancy and behavioural intention was stronger for women, particularly younger women. This particular pattern was not discernible during the current analysis.

High experience of using the system as well as experience of using EOCISs in general also strengthened the relationship between facilitating conditions and performance expectancy. Age also appeared to strengthen this relationship. This contrasts with many previous technology acceptance studies, which have not reported these moderating effects. There were no significant moderation effects from gender and emergency management experience.

Experience of using the system and general emergency management experience appeared to strengthen the relationship between facilitating conditions and symbolic adoption. However there was no significant influence from previous EOCIS experience. Although the original UTAUT model (Venkatesh et al., 2003) ignored this relationship, Venkatesh et al. (2012) observed that use experience lessens the relationship between facilitating conditions and behavioural intention. This previous finding was contradicted in the current research. The current research also found that the relationship between facilitating conditions and symbolic adoption is significantly stronger for men as well as for older age end-users. This observation partially replicates research by Venkatesh et al. (2012), who identified a similar age-related pattern amongst female end-users but not for men.

The current research explored moderation effects on the relationship between information quality and performance expectancy. Significant moderation of this relationship was attributed to age, gender and system use. Older age appeared to strengthen the relationship while system experience appeared to weaken the relationship. Likewise, male gender appeared to strengthen the relationship, while end-users older than 50 years were associated with a significantly weakened relationship between information quality and performance expectancy. Information quality was identified as one of the key antecedent variables in research by Moores (2012). However Moores (2012) did not check for moderated variations in the effect of information quality. The current research provides new insights in this regard.

Finally, the current analysis explored the influence of moderating variables on the relationship between performance expectancy and symbolic adoption. Experience of using the system appeared to weaken this relationship. This observation differs from research by Venkatesh et al. (2003) which did not identify any significant moderating influence from experience of using the system. The way that the relationship between performance expectancy and symbolic adoption appears stronger for females compared to males, together with the absence of a moderating effect from age, also differ from these initial UTAUT precedents. Venkatesh et al. (2003) had previously observed a stronger effect of performance expectancy amongst younger men in particular.

Similar moderation effects were observed when conducting the same analysis for each of the three different national contexts included in this study: New Zealand, USA and Australia. However, in the absence of a larger sample from each of these contexts, we were unable to accurately determine how these moderating effects varied by national context. This inability to more accurately model contextual and product influences forms one limitation of the current research. Likewise, the current model has been tested with EOCISs which are still progressing between the initiation and acceptance stages of implementation. The current findings may therefore not apply to the acceptance of systems in the final stages of implementation or to the behaviour of end-users across the entire implementation cycle outlined by Cooper and Zmud (1990). This represents an opportunity for further research, employing a longitudinal approach to the current model by gathering data at more than one point in time. This would help understand how end-users' acceptance-related perceptions and behaviours vary across different phases of EOCIS implementation.

6. Conclusion

The validated research model displayed in Fig. 5, explains several substantial implications for the implementation of EOCISs in a range of English-speaking contexts. One of the most important implications is how social influence, within peer groups and organisations as a whole is likely to have a directly positive impact on technology uptake. This impact appears unlikely to be complicated by performance expectancy. Many more practical implications, such as the importance of a range of facilitating conditions can be drawn from the validated model. We observed that the model of technology acceptance developed during the current research was moderated by end-user profile characteristics such as age, gender and user experience. This indicates that different cohorts of end-users may attach different weights to various factors that influence their use of the system. These moderating effects suggest that to facilitate end-users' acceptance throughout an implementation process, an implementation team should consider the different needs of end-users alongside relevant behavioural implications. It is important for the system implementers to identify profile and behavioural differences of the cohorts of end-users, to more confidently manage organizational change required during system implementation.

In contrast to many prior research into technology acceptance, the current research has highlighted the significant impact of end users' performance expectancy. This factor appeared to substantially mediate end-users' attitude towards accepting or rejecting EOCISs. It is evident that performance expectancy significantly influences the relationship between other key end-user acceptance factors and that this can considerably alter the levels of end-user acceptance of an EOCIS. The current findings therefore provide clear guidance for system implementation, to pay close attention and make necessary arrangements to enhance the performance expectancy of end-users during implementation of EOCISs.

Both examples outlined above show how EOCIS implementation professionals can use the current findings to evaluate and adjust their implementation process. The current technology acceptance model also provides these professionals with a tool to statistically monitor changes in relevant end-user attitudes during certain stages of system implementation. This approach, to considering statistically robust insights about the EOCIS implementation process, could prevent many pitfalls of system implementation before they occur. There may be other, more generic potentials such as training early adopter groups of middle-aged personnel. This would fulfil identified needs for facilitating conditions, while maximizing the social influence of middle-aged personnel as early adopters amongst the rest of the organisation. In the longer term, with reference to clear needs for EOCIS utilisation, this kind of evidence-informed approach to system implementation is likely to maximise resulting gains in emergency management performance.

The current findings build on our summary of literature surrounding the TAM and UTAUT models of technology acceptance, to suggest that these technology acceptance theories remain fundamentally incomplete. For example, prior iterations of these models have only rarely explored the possibility of significant mediation. The current analysis makes it clear that future research will benefit by more carefully considering mediator effects, in both highly specific and more generic research contexts. The current research model explained a considerable higher variance of 65 percent with mediator effects included. This model could be further strengthened by considering some of the factors exclusive to the design of emergency management information systems (Van de Walle et al., 2010). In particular, future research using the current research model in the context of technologies and systems supporting EOC personnel may consider incorporating the influence of failure factors specifically related to the information system supporting stressful and time critical environments: attention tunnelling, misplaced salience, complexity creep, errant mental models, out of the loop syndrome and contextual stresses as identified by Endsley et al. (2011). Endsley et al. (2011) outlined how attention tunnelling occurs when end-users fix their attention on specific elements of information while becoming blinded to other elements. This can be problematic when important information is not given the required level of prominence. The use of new systems in stressful environments is also severely affected when end-users form inadequate internal representations of how those systems function, in what Endsley et al. (2011) referred to as errant mental models. An errant internal representation can be particularly harmful when the user does not know that their understanding of the system is flawed. These users' system use becomes much more error prone due to a dynamic called out of the loop syndrome. This syndrome occurs when end-users of highly automated systems lose touch with the status of elements they are trying to control. This marks one of several situations where the use of system itself could exacerbate negative aspects of work related contextual stresses.

Prasanna (2010) outlined several aspects of system design which may improve effective system implementation. For example, attention to the scalability of the system, to adjust between small and large scale events (Prasanna, 2010), may help mitigate failure due to attention tunnelling and contextual stresses. Failure factors may also be mitigated through attention to flexibility between equally supporting end-users playing the same role with different levels of experience and providing equal level of support for responding to different types of events or disasters. These are important design considerations when developing and implementing an emergency response system. Further research could incorporate these design factors, either as a variable or a proxy variable, to further develop the proposed model and better explain end-users' acceptance of EOCISs. Prior to incorporating these context-specific variables, it would be essential to conduct a preliminary study to identify appropriate statistical measures. This preliminary approach to developing innovative measures concerning information technology for emergency management has recently been exemplified by Huggins, Hill, Peace, and Johnston (2015). Their pilot research produced a set of reliable, and theoretically relevant, measures for assessing the relationship between emergency management performance and information display design which can now be used in much larger scale studies.

The aim of this particular study was nonetheless to test generic technology acceptance models in the emergency domain. Factors exclusive to the domain of emergencies were beyond this particular scope. The authors are now preparing a second study which will reconcile literature on unique aspects of emergency management functions with a range of research into the use of information systems. By doing so, the authors aim to strengthen the explanatory potential of the current research model. Further research can also avoid another key limitation of the current research and most extant technology acceptance literature. As stated by Pearl (2000), directionality between antecedents and dependent variables in a structural model is difficult to establish through statistical analysis alone. This limitation can be overcome by collecting initial longitudinal data for antecedent factors, before collecting data on resulting attitudes and usage behaviours.

As stated, the current research combined elements of both the UTAUT and TAM models of technology acceptance. The statistically robust nature of the resulting model suggests that the original UTAUT model should not be uncritically adopted, as a model to universally explain technology acceptance in different conditions and contexts. Instead, it seems important to carefully combine strengths of UTAUT with the strengths of other technology acceptance models and other context specific factors. Context specific factors are not usually considered in generic technology acceptance research, but will lead to more appropriate and accurate interpretations.

The current findings include significant variations in the antecedents of technology acceptance, due to various moderating effects of age, gender and experience. This contrasts with previous technology acceptance literature where moderating effects have not generally been explored. The scope of the current research does not extend to understanding the reasons for such variations. However it is recommended that future research examines reasons for such variations of influence in the context of emergency management, before making recommendations for evidence-informed management practice.

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