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ORIGINAL PAPER

Electronic medical record systems: decision support examination framework for individual, security and privacy concerns using multi-perspective analysis

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Abstract

Electronic medical record (EMR) is currently a popular topic in e-health. EMR includes the health-related information of patients and forms the main factor of e-health applications. Moreover, EMR contains the legal records that are created in the medical centre and ambulatory environments. These records serve as the data source for electronic health record. Although hospitals utilise the EMR system, healthcare professionals experience difficultly in trusting this system. Studies devoted to EMR acceptance in hospitals are lacking, particularly those on the EMR system in the contexts of privacy and security concerns based on multi-criteria perspective. Thus, the current study proposes a decision support examination framework on how individual, security and privacy determinants influence the acceptance and use of EMR. The proposed framework is based on a multi-criteria perspective derived from healthcare professionals in Malaysia as frame of reference. The framework comprises four phases. The sub-factors of individual, security and privacy determinants were investigated in the two initial phases. Thereafter, the sub-factors were identified with uniform multi-criteria perspective to establish a decision matrix. The decision matrix used individual uniform as basis to cluster the sub-factors and user perspectives. Subsequently, a new 'multi-criteria decision-making (MCDM) approach' was adopted. Integrated technique for order of preference by similarity (TOPSIS) and analytic hierarchy process (AHP) were used as bases in employing the MCDM approach to rank each group of factors. K-means clustering was also applied to identify the critical factors in each group. Healthcare professionals in Malaysia were selected as respondents and 100 questionnaires were distributed to those employed in 5 Malaysian public hospitals. A conceptual model adapted from Unified

Highlights • Identify the privacy, security, and individual factors that could effect on acceptance and use of an EMR system in Malaysian public hospitals.
• Established a decision matrix incorporating the sub-factors and multi-criteria perspectives.
• Utilized decision-making technique based on performed decision matrix to rank each group of factors.
• Applied the K-mean clustering in order to identify the critical factors in each group.
• SEM was used to analyze data related to examine the influence of factors on EMR acceptance and use.

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theory of acceptance and use of technology 2 (UTAUT2) was employed to clarify the connection between individual, privacy and security determinants and EMR system acceptance and use in the selected context. After collecting the data sets (363), structural equation modelling was used to analyse data related to EMR acceptance and use. Results are as follows. (1) Five determinants (i.e. data integrity, confidentiality, non-repudiation, facilitating conditions and effort expectancy) exerted an explicit and important positive effect on EMR acceptance and use. (2) Three determinants (i.e. unauthorised, error and secondary use) exerted a direct and significant negative effect on EMR acceptance and use. (3) Three other determinants (i.e. authentication, performance expectancy and habit) insignificantly affected the behavioural intention of healthcare experts in Malaysia to use EMR.

Keywords E-healthcare · Users behaviour · Security and privacy · Electronic medical records · Multi-criteria decision-making and structural equation modelling

1 Introduction

The term e-health, which emerged in the early twenty-first century, pertains to applying the utilisation of modern information and communication techniques to the conveyance of medical services in the health sector [1, 2]. E-health needs multidisciplinary advancements, such as telecommunication, computer science and instrumentation, to exchange medical data across expansive geographic regions [3, 4]. E-health application empowers global thinking and networking and advances healthcare on the local, regional and national levels [5, 6]. Healthcare improvement offers several benefits, including operational healthcare efficiency and patient care quality. Healthcare providers, such as doctors, are considered the most important influencers in pushing e-health initiatives. If healthcare providers do not accept and use e-health, then the benefits of this practice cannot be enjoyed [7]. ‘Electronic medical record’ (EMR) and ‘electronic health record’ (EHR) are terms that are distinct from each other and are separately utilised, although both records contain the health-related information of patients and form the main factor of e-health applications [8–13]. All groups of healthcare providers, such as physicians, nurses and pharmacists, can utilise EHR and EMR [14]. This study focuses on EMR (i.e. the legal record created in medical centres and ambulatory environments), which serves as the data source for EHR. Through EHR, medical information can be easily shared amongst stakeholders and patient information can be accessed and updated as a patient undergoes various modalities of care. Healthcare providers, patients, employers or insurers/payers are regarded as stakeholders, along with the government [15, 16]. Health information technology (HIT) can potentially enhance the characteristics, efficiency and outcomes of healthcare, along with patient safety, whilst reducing the cost [17–25]. Despite the implied benefits, the availability of HIT systems is restricted, whilst the available ones are improperly implemented [26, 27]. Additionally, HIT acceptance is low, particularly in developing countries. The manner by which the intended users perceive a system should be explored before developing or implementing the system, given that user perception positively affects the actualisation of any system [26, 28–33]. The common issues in EMR system are security, privacy and confidentiality [34–38]. To illustrate, physicians are concerned that unauthorised people could access patient information stored in the EMR system and exploit the information, thereby resulting in legal complications [39] because patient records are confidential. [40] claimed that physicians are concerned with security/confidentiality issues over the actual patients. The majority of the physicians who use EMR favours paper records than the EMR system because the former is more secure and confidential. Such preference shows the influence of privacy and security concerns on EMR acceptance. Without privacy assurances, patients may have reservations on whether they should provide information to the healthcare provider for improved healthcare or withhold information to prevent inappropriate use [41–52].

2 Literature review

To the best of our knowledge, an integrated research on EMR acceptance and use, privacy and security, and MCDM has yet to be conducted. Figure 1 illustrates the perspective that the current study considers in the EMR acceptance model. This model includes individual, privacy and security factors. These three groups of factors will be analysed using multi perspectives that represent all stakeholders of this type of systems (e.g., pharmacists, physicians, nurses and laboratory employees). These factors should be analysed based on all the perspectives to make the system acceptable by the majority of users. The MCDM approach will be utilised to identify the critical factors in each group based on multi perspectives.

This section is segmented into three parts. The studies related to EMR acceptance and use are reviewed firstly, followed by research on privacy and security in the EMR context. Studies that apply the MCDM approach are reviewed last.

2.1 Studies on EMR acceptance and use

Eleven empirical studies are devoted to EMR acceptance and use. Two of these studies explore the organisational factors that affect the EMR acceptance of physicians [53, 54]. [55,

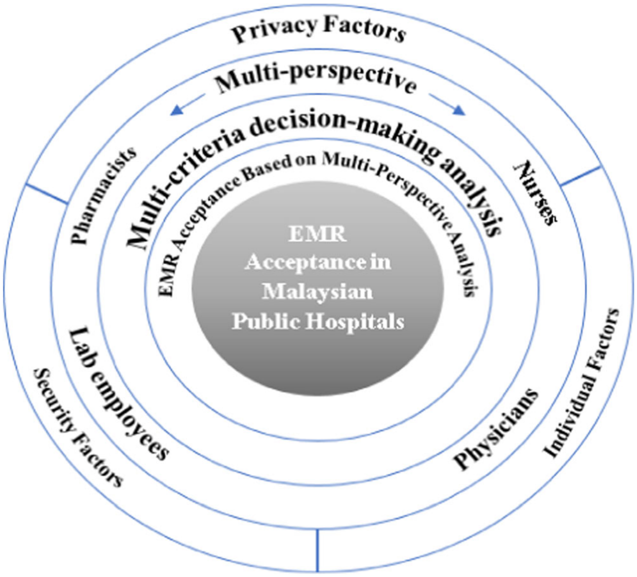

Fig. 1 EMR acceptance model

56] applied the unified theory of acceptance and use of technology (UTAUT) in the context of EMR acceptance and use from a physician perspective. They added privacy to the UTAUT model. Moreover, [57] Only applied UTAUT model from top and middle managers perspectives. [58] analysed the technology acceptance model (TAM) as the dependent variable with threat and inequity as independent variables. [59] adopted TAM to study the effect of individual capabilities (i.e. self-efficacy and perceived behavioural control) on EMR acceptance from a doctor's perspective. [60] used TAM to determine the effect of added involvement, user-patient, user-autonomy, resident background and restricted access on EMR acceptance from a healthcare professional's perspective. [61] employed the TBP model and added perceived privacy. [62] Integrated between two theory UTAUT and TAM to confirm the factors that influence users' intentions to utilize a mobile EMR system from doctor and nurses. [63] Integrated between UTAUT and Innovation Diffusion Theory (IDT) and added two factors which are information characteristics and system characteristics from users of EMR system.

Previous studies have investigated organisational factors. [56, 58] addressed the privacy and security concepts in general. [56] focused on privacy risk, whereas [58] discussed threat and inequity. Nevertheless, no empirical studies have been conducted that extensively explore privacy and security issues. EMR has many key constraints apart from privacy and security that warrant attention from research communities [64]. Moreover, the majority of studies on EMR acceptance and use are based on a single perspective, such as that of doctors, nurses, or administration staff members. If a multi-perspective approach is employed, then a comprehensive understanding of the issues can be achieved, thereby providing insights into the needs of each user group.

2.2 Studies on privacy and security concerns in EMR

EMR studies can be classified into three types, namely, (1) empirical study (2) conceptual model and (3) review paper. Under the first type, [58] addressed threats in EMR acceptance, whilst [56] discussed the privacy concern in EMR acceptance. [65] employed the CFIP model in the EMR context. Under the second type, [66] proposed a conceptual model that includes security/confidentiality. [34] established a framework that features security, privacy, confidentiality and unauthorisation. The review papers on EMR acceptance and use allude to privacy and security issues, particularly confidentiality, authorisation, threat, unauthorisation, integrity, availability, unauthorised data collection and secondary use, error and privacy risk [67–70]. Despite several review papers, in depth investigation for privacy and security issues have been conducted in the context of EMR acceptance. Although privacy and security concerns affect the acceptance of e-health [71], these issues have yet to be studied extensively. Moreover, all previous studies on privacy and security contexts are based on a single perspective and are multi-dimensional.

2.3 Studies using the MCDM approach

Studies on EMR acceptance that use the MCDM approach have yet to be conducted. [72] specified the critical determinants of the EMR system to aid healthcare organisations, specifically hospitals, in their understanding of the behaviour of key users towards EMR acceptance. The study used analytic hierarchy process (AHP) to select the critical factors (i.e. people, organisation and implementation). A questionnaire from an expert perspective was distributed to the stakeholders. TOPSIS was also adopted to select the critical determinants from another single perspective (i.e. that of physicians). [73] provided additional insights into the potential factors that facilitate or inhibit the health information system (HIS) in Malaysia. The study used AHP to evaluate technological, organisational, environmental and human factors from senior executives in the healthcare industry, particularly on the hospital perspective. [74] identified, categorised and analysed the meso-level factors introduced by [75]. These factors are perceived by physicians with regard to the EMR system and are employed to clarify the topic of primary care setting. Thereafter, these factors are ranked by using TOPSIS to determine the aspects that are imperative in the EMR system based on a physician perspective. No study has addressed the privacy and security concerns in EMR acceptance and use of MCDM. The majority of the related studies use MCDM to rank the factors from a single perspective.

The number of studies on EMR acceptance and use is inadequate and privacy and security concerns should be addressed from multiple perspectives. Given that the majority of previous studies merely provided a general discussion of privacy and security issues, an in-depth investigation is required to understand these concerns. Overall, no existing study has addressed privacy and security factors as multidimensional in the context of EMR system based on multiperspective analysis. The problem with single perspective is addressing the requirements for one type of group users and solving the problem of only one user.

3 Research model and hypothesis development

3.1 Theories and models of technology acceptance

[76] stated that 'theories of technology acceptance provide a set of explanatory variables that can be adopted to predict a particular phenomenon'. By contrast, TAM provides 'a systematic description for system and theory, or a phenomenon that accounts for its known or inferred properties that may be utilized for further evaluation of its characteristics. A model also refers to any abstract representation of some portion of the real world, constructed to understand, explain, predict, or control a phenomenon being investigated'. These theories and models are discussed in the following sections.

3.1.1 Theory of reasoned action (TRA)

According to [77] proposed TRA, a fundamental theory on human behavior. As a well-designed and validated behavioral prediction model, TRA is successfully employed in predicting user behavior. The relationship among attitudes, subjective norm, and behavior is evaluated using TRA. This theory supposes that specific intentions and behavior can be predicted by attitudes toward behavior and subjective norm.

3.1.2 Theory of planned behavior (TPB)

According to [78] proposed TPB, a successor of TRA, proposes a third independent determinant of intention, i.e., perceived behavioral control (PBC). This determinant is evaluated by the availability of skills, resources, and opportunities, as well as the perceived importance of those skills, resources, and opportunities to achieve outcomes [79]. Kripanont indicated that the probability that a person will perform a desired action can be increased by changing attitude, subject norm, and PBC, thereby increasing the chance of the person actually performing it.

3.1.3 The technology acceptance model (TAM)

TAM is an adaptation model of TRA [80]. This model describes the acceptance of users of information systems, and it is an intention-based model. TRA supposes that beliefs affect attitudes, which in turn indicates intentions that result in behavior. TAM considers the relationships among belief, attitude, intention, and behavior in modeling the IT acceptance of users [81]. Perceived usefulness (PU) and perceived ease of use (PEOU) are denoted by TAM as the main factors affecting IT acceptance behavior.

3.1.4 UTAUT

The limitations of TAM, TAM2 and TAM3 are improved through the introduction of UTAUT [82]. Eight common models of user interaction represent the basis of UTAUT: motivational model, TPB, TAM, TRA, model of personal computer utilisation, social cognitive theory, innovation diffusion theory and a hybrid model that integrates constructs from TPB and TAM. 'Performance expectancy, effort expectancy, facilitating conditions, and social influences' are proposed as the four key constructs for describing and prophesying user acceptance of tested technology. Four key moderating factors, namely, 'age, gender, experience and voluntariness of use', are also considered. [82] described performance expectancy as 'the degree to which an individual believes that the use of a system will help in attaining high job performance'. Effort expectancy pertains to 'the degree of ease associated with the use of the system'. Social influence denotes the extent to which a person considers the opinion of others on whether he or she must utilise technology. Moreover, facilitating conditions represent the extent of availability of technical support for using a new technology. The various modifications of the model in the last decades have revealed the significance of various factors, namely, 'hedonic motivation, price value and habit' [83, 84] and 'cognitive individual differences, learning and teaching styles' [85]. [86] conducted a meta-analysis of UTAUT and confirmed the initial findings obtained by [82] on the relationships amongst the five constructs of UTAUT (i.e. 'effort expectancy, performance expectancy, facilitating conditions, social influence, and intention to use'. However, they indicated that the outcomes of empirical studies are questionable, particularly in the social sciences, whilst the model accuracy is dubious.

3.1.5 UTAUT2

TAM, UTAUT and TPB are applied in studying EMR acceptance and use. By contrast, only a few studies have applied UTAUT2 to understand EMR acceptance and use and Moreover, the extensions in UTAUT2 generate considerable improvement in the variance explained in behavioural intention (56% to 74%) and technology used (40% to 52%) [84] and UTAUT2 was criticized for not including privacy, security, and trust in its conceptualization [87]. Thus, the present study employs UTAUT2. In 2012, [84] modified the

UTAUT model to become considerably consumer centred, thereby resulting in UTAUT2. UTAUT2 is tailored to the context of consumer acceptance and use of technology. In UTAUT2, the constructs are moderated only by gender, age and experience. Voluntary use is excluded because the target population is not required to utilise the technology. UTAUT2 also produces three new constructs, namely, price value, hedonic motivation and habit. Hedonic motivation and price value elucidate behavioural intention, whilst habit rationalises behavioural intention and use behaviour. Nevertheless, [88] reiterated that price value should be excluded if a system is freely available. Price value is excluded in the current research because the EMR system is available to healthcare professionals for free.

Our analyses indicate that the majority of the published studies utilised TAM or extensions of TAM in consumer health information [89, 90]. No studies have designed UTAUT and TAM for the consumer field. Preferably, we required a model developed for the consumer's utilisation context and UTAUT2 to gain ideal results [84]. The studies that use an UTAUT2 extension have described its benefits in evaluating the critical determinants for the adoption of the EHR portals but did not consider privacy and security issues [89, 91].

3.2 Individual factors

UTAUT2 includes 'performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit'. [92] regarded these factors individually. UTAUT2 is applied in the healthcare context to explore HIT acceptance [93–95]. The present study considers these factors to be individual factors.

3.2.1 Performance expectancy

Performance expectancy pertains to the benefit that an individual perceives to obtain by utilising a technology in performing a certain activity [84]. Since performance expectancy is a predictor of behavioural intention, it will be added value to implement UTAUT and UTAUT2 models. When applied in health environments, performance expectancy is confirmed as an ideal predictor of behavioural intention. That is, patients who consider e-health beneficial and a main source of information, are more receptive to use this system than those who perceive technology negatively [96, 97]. The reference studies the acceptance of pharmacokinetics-based clinical decision support systems of physicians in Taiwan discovered performance expectancy impacts behavioural intention to utilise the system more robustly than expected [98]. Therefore, the following hypothesis is formulated:

- H1a. Performance expectancy (PRE) has a positive effect on intention to utilise EMR (INTENTION).

3.2.2 Effort expectancy

Effort expectancy refers to the manageable usage of a technological activity [82]. Previous studies have indicated e-health's ease of use (i.e. simplicity of using e-health) as an essential factor [99]. [97] suggested that patients easily accept e-health platforms that are manageable. Early research has revealed that effort expectancy influences system use. Additionally, effort expectancy significantly and positively affects the intention to utilise systems for healthcare information [100], adverse event reporting [101] and clinical decision support [98]. Thus, the following hypothesis is proposed:

- H1b. Effort expectancy (EFE) has a positive effect on intention to utilise EMR (INTENTION).

3.2.3 Social influence

Social influence is 'the effect that a person held to be important to an individual has on the decision of that individual to use a technology activity' [82]. In the case of e-health, many peer-support communities and online forums can influence consumer decisions to utilise e-health platforms. People in similar situations and health conditions can share their opinions and experiences through these online communities [96, 102]. The research on HIS approval [103] has revealed that the behavioural intention of hospital employees are socially influenced. [101] indicated that 'behavioral intention to utilize an adverse event reporting system' is positively affected by a subjective norm. Thus, the following hypothesis is developed:

- H1c. Social influence (SOCI) has a positive effect on intention to utilise EMR (INTENTION).

3.2.4 Facilitating conditions

Facilitating condition is the perception of the available support in using a technological activity [82]. Consumers who use online health services are hindered by their resources when accessing these platforms [99, 104], thereby indicating that people who can use e-health technologies favour the adoption of telehealth services. [98] presented that facilitating conditions positively influence the utilisation behaviour of pharmacokinetics-based clinical decision support systems of physicians. [105] revealed that perceived behavioural control (PBC) considerably determines physicians' behavioural intention of using PDAs. PBC represents facilitating statuses as an immediate determinant of use. Thus, the following hypothesis is formulated:

- H1d. Facilitating conditions (FCC) has a positive effect on intention to utilise EMR (INTENTION).

3.2.5 Perceived enjoyment or hedonic motivation

Perceived enjoyment or hedonic motivation is defined as 'the intrinsic motivation of an individual to obtain fun or pleasure from using a technological activity' [84]. Behavioural intention is strongly predicted by hedonic motivation [84]. E-health consumers understand the importance of this construct to e-health consumers and such understanding can be a sufficient reason for adoption [106]. Thus, the following hypothesis is proposed:

- H1e. Hedonic motivation (HEDO) has a positive effect on intention to utilise EMR (INTENTION).

3.2.6 Habit

Habit is a behaviour's automation learned from prior experiences, thus, habit is a predictor of various technological adoptions [84]. The following hypothesis is proposed:

- H1f. Habit (HBT) has a positive effect on intention to utilise EMR (INTENTION).

3.3 Security and privacy factors

They feel overwhelmed that the security and privacy of patient records have not been addressed well. Moreover, security and privacy issues remain as a barrier to EMR adoption [107]. Moreover, people who are involved in the EMR system can follow the lack of clear security standards. Understanding and possessing the correct strategies to deal with such barriers ensure the successful acceptance and use of EMR [108]. Security and privacy factors are important when accepting and using medical assistive technologies [109]. EMRs have significant advantages but current technologies are not well employed. Thus, full potential is not realised, whilst patient privacy is not maintained. This domain has a few key constraints and challenges, such as the security and privacy of EMRs; hence, such constraints and challenges remain open and require considerable attention from the research community [64, 110].

3.3.1 Security factors

'Authentication, data integrity, confidentiality, authorization, non-repudiation, and availability' should be incorporated into a system's security procedures and policies by medical IT solutions and be considered security factors [111–131].

Authentication Authentication is required as protection from the illegal access to the condition of patients and can provide high levels of privacy for patients. Patients and health workers should fulfil authentication requirements. Patient identification is important for receiving proper treatment, whilst authorised health workers should be identified and unauthorised personnel should be prevented from gaining access to patient records. [132] stated that the privacy of clients and originality of other documents should be ensured for validity.

- H2a. Authentication (AUT) has a positive effect on intention to utilise EMR (INTENTION).

Data integrity Integrity means that authorisation is needed to modify data and is different from the referential integrity of databases. Examples of violation of integrity include an employee who modifies his salary in a payroll database, an employee who accidentally or maliciously erases critical data files, a computer virus that contaminates computers, someone who can cast significant votes in an online poll and an unauthorised user who is involved in vandalising a site [133, 134]. Information security professionals should formulate methods to control and prevent integrity errors [135, 136].

- H2b. Data integrity (DATA) has a positive effect on intention to utilise EMR (INTENTION).

Confidentiality Information confidentiality prohibits unauthorised users to reach, utilise, copy or expose information when necessary [136, 137]. Data confidentiality keeps information only for authorised people and systems [138, 139]. Confidentiality ensures that only authorised people can gain access to confidential information.

- H2c. Confidentiality (CNF) has a positive effect on intention to utilise EMR (INTENTION).

Non-repudiation Non-repudiation denotes the intent to satisfy contract obligations and implies that receiving and sending transactions cannot be denied by the parties involved [140]. Digital signatures and encryption can be used by electronic commerce in establishing non-repudiation and authenticity [135].

- H2d. Non-repudiation (NRP) has a positive effect on intention to use EMR (INTENTION).

Availability Availability refers to the accessibility and function of information, computing systems that process the information and security controls that protect information [135]. An information system functions correctly when information is available upon request [135]. Therefore, systems that store and process information, security controls that protect information and channels that facilitate access to information should function correctly [141]. Systems that are highly available should constantly be available and prevent service disruptions owing to hardware failures, system upgrades and power outages. Availability can also be ensured through the prevention of denial-of-service (DoS) attack [140, 142].

- H2e. Availability (AVAIL) has a positive effect on intention to utilise EMR (INTENTION).

3.3.2 Privacy factors

The privacy and security of health information of patients are critical in the electronic healthcare environment [143, 144]. Authentication, availability, confidentiality, authorisation, non-repudiation and data integrity are the most frequent issues in health records. Moreover, health information systems rarely measure concerns on privacy concern using a validated measure. However, the emergence of many privacy concern measures is led by other disciplines' information on privacy studies. A high degree of overlap in terms of dimensions is measured. 'Collection, improper access, errors, and unauthorized secondary utilize' are the most popular dimensions that previous studies have analysed [145]. Every measurement is outlined on its significance to privacy in the medical context. The privacy concern of all types of personal information is escalated as information is increasingly digitised. The CFIP construct is minimally used in the IS research and not tested in other fields. The CFIP model includes (1) unauthorised access, (2) data collection, (3) secondary use and (4) errors. Moreover, CFIP is the most used model in the EMR context owing to its focus on the practices of an organisation.

Unauthorised Access EMR aims to enhance the sharing and accessibility of health records amongst authorised facilities and individuals [146]. Computerised medical information becomes increasingly valuable and requires protection from unauthorised access because of the integrated information collected from various databases [147]. Unauthorised access refers to the unauthorised view or work on readily available data and is the people's concern [148]. Several medical professionals have mentioned that patient information is often released to people without authority [146]. Individuals should only be permitted to obtain personal information when they 'need to know' before accessing personal information [148, 149]. However, threats of unauthorised access to information through technical means is possible in health facilities [150].

- H3a. Unauthorisation (UNAU) has a negative effect on intention to utilise EMR (INTENTION).

Collection Many are concerned with the amount of personally identifiable data in EMRs [148]. [151] included the collection of information as information privacy component. Smith, Milberg and Burke suggested that the collection of information is a dimension of people's concern for the privacy of information. [152] explained that privacy concerns may be associated with particular information practices, such as collection methods. Easy data collection, storage and transmission on electronic networks are significant privacy risks [153]. Hence, the following hypothesis is proposed:

- H3b. Collection (COL) has a negative effect on intention to use EMR (INTENTION).

Secondary use Individual information is occasionally collected and used outside its original purpose without permission from the concerned individuals [149]. Privacy concerns are likely intensified when information is not solely restricted to the original purpose of its collection [154]. Therefore, privacy issues are likely to increase when organisations process data beyond what is required by the prime transaction [155]. The use of personal data without authorisation evokes negative responses even if the data are controlled internally by an organisation [149]. The present study refers to the secondary use of data, in which people are substantially concerned with the collection of personal health information for one aim but is utilised for another purpose without authorisation [148]. The following hypothesis is proposed:

- H3c. Secondary use (SCU) has a negative effect on intention to use EMR (INTENTION).

Errors Error denotes those that are intended and unintended in the personal health data of patients collected by health amenities and concerns individuals who are insufficiently protected against such errors [148]. People may be aware that their information is being collected [154] but they may have concerns because of an organisation's inadequate effort to mitigate problems that contribute to personal data errors [148, 149]. Deliberate errors may exist but the majority of privacy-related issues come from accidental personal data errors [148, 149]. The following hypothesis is proposed:

- H3d. Error (ERR) has a negative effect on intention to utilise EMR (INTENTION).

The main focus of this phase involves extracting security, privacy and individual problems that affect EMR acceptance and use. Lastly, 15 issues related to individuals, privacy and security were selected. Although the issues in the EMR system presented are incomplete, they represent the prevalent concerns for the system. The conceptual model of this study is dependent on the developed hypotheses.

4 Proposed conceptual model

Figure 2 presents the research model, which shows the hypotheses and relative paths.

5 Methodology

The main aim of this study is to investigate how individual, security and privacy determinants influence EMR acceptance and use. Critical determinants that will be identified are based on multi perspectives using MCDM. The final EMR acceptance model will be built based on the critical determinants.

The presented methodology is based on multi-criteria perspectives derived from healthcare professionals in Malaysia as frame of reference.

Initially, our study reviews the privacy, security and individual factors that could affect the acceptance and use of an EMR system in Malaysian public hospitals. The three groups of factors that are identified with the multi perspectives (user perspectives) will be the main components of the decision matrix that will be developed. The context represents a crossover between multi perspectives (users' perspectives) as criteria and three groups of factors as alternatives. Thereafter, the MCDM technique based on an integration of TOPSIS and AHP will be used to rank each group of factors to determine the most important in each group. Lastly, the important factors identified in the three groups will be adopted in the development of the final model, which is based on multi perspectives for the acceptance of the EMR systems.

5.1. This section reviews previous studies that have investigated the privacy, security and individual factors that can influence EMR acceptance and use. However, several issues limit the scope of our study. Moreover, this research applies only to the aforementioned determinants for EMR acceptance and use.

5.2. ***Here***, we define the multi-perspective criteria for the factors (i.e. privacy, security and individual) that can influence EMR acceptance and use. A decision matrix is developed based on the crossover between the factors and multi-perspective criteria. The incorporation of various healthcare viewpoints provides the advantage of various knowledge and experience [156, 157]. Nevertheless, evaluating information systems, such as EMRs, within a team setting is often difficult because of the many outlooks present in a team [158] and [158].

EMR is 'crucial for providing patients' medical histories and it includes one or more computerized clinical information systems that collects, stores, and displays patient information' [34]. Examples of such systems include 'Biomedical Informatics Ltd, clinical information systems (CIS), financial information systems (FIS), laboratory information systems (LIS), nursing information systems (NIS), pharmacy information systems (PIS), picture archiving communication systems (PACS), radiology information systems (RIS), and computerized clinical information system components' [34]. However, each HIS component differs based on the departments and types of users in hospitals [159].

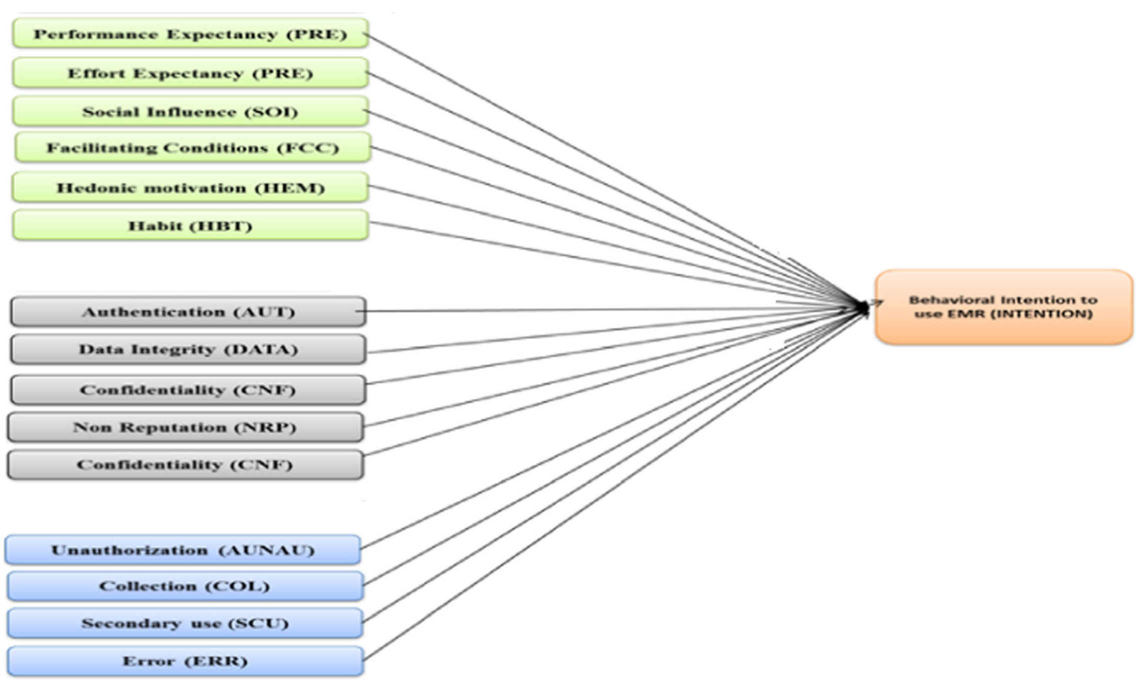

Fig. 2 Research model

The extant literature addresses EMR acceptance and use from several single perspectives, such as those of physicians, nurses, pharmacists and laboratory employees. However, only a few studies on EMR acceptance and use incorporate uniform multi-perspective criteria, particularly in terms of the privacy, security and individual contexts. Consequently, we develop a decision matrix with two parts. The first part involves alternatives that comprise the privacy, security and individual determinants as identified by previous studies. The second part introduces the multi perspectives of physicians, nurses, pharmacists and laboratory employees. This study integrates the three groups with multi perspectives in a single decision matrix.

5.3. This phase develops a new 'multi-perspective decision-making methodology' depending on the issues identified from the previous phases. [160] defined MCDM as 'an extension of decision theory that covers any decision with multiple objectives'. Hence, MCDM is a methodology for assessing alternatives on individual and often conflicting criteria and combining these alternatives into an overall appraisal. Moreover, [161] defined MCDM as 'an umbrella term to describe a collection of formal approaches, which seek to take explicit account of multiple criteria in helping individuals or groups explore decisions that matter'. Multi-criteria analysis, which is a sub-discipline of operational research that explicitly considers several criteria in decision-making environments, occurs in different actual situations of a medical record [161]. Several useful techniques can be applied in actual MCDM issues. These techniques assist decision makers (DMs) organise outstanding problems and provide prioritising, scoring and analysis of alternatives [9]. Accordingly, the scoring of suitable alternatives is performed in the current study. Several MCDM methods are reviewed. The most popular MDCM methods that use different concepts in accordance with [162–167]. To the best of our knowledge, none of these methods is used to rank each group of the individual, security and privacy factors of EMR acceptance-based multi-perspective analysis. Figure 6 shows the advantages and disadvantages of the MCDM techniques based on [162, 168–180].

The MADM/MCDM methods can also solve the scoring problem for factors based on multi-perspective criteria in medical records. In any MADM/MCDM ranking, the fundamental terms should be defined and these terms include a decision or evaluation matrix (EM), alternatives and criteria [162, 212]. EM that comprises m alternatives and n criteria should be created. Given the intersection of each alternative and criteria asx_{ij}, we obtain the matrix $(x_{ij})_{m*n}$.

$$DM/EM = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{array}$$

where, A_1, A_2, …, A_m are the possible alternatives rated by DMs (i.e. sub-factors of privacy, security and individual); C_1, C_2, …, C_n are the criteria against which each alternative performance is measured (i.e. perspectives of physicians and nurses) and x_ij represents the value of alternative A_i with regard to the C_j criterion, whilst C_j has W_j as a weight. Various procedures rank the alternatives, whilst the application of each of these procedures depend on the method used [214–217].

The effect of the determinants on the EMR system is evaluated using multi-perspective criteria involving physicians, nurses, pharmacists and laboratory employees. However, each factor has a multi perspective and each DM has different weights for these perspectives. Therefore, selecting the suitable factors based on multi perspectives is problematic. On the one hand, EMR users are not equal with respect to the use of EMR systems. For example, physicians are regarded as the core users of such systems. Accordingly, they have more rights than other users. On the other hand, factor selection (i.e. from privacy, security and individual) is a multi-perspective problem, in which each factor is deemed an available alternative for DM.

From this viewpoint, TOPSIS is suitable for cases with numerous attributes and alternatives [210, 211, 213]. Specifically, TOPSIS application is convenient when objective or quantitative data are provided. The TOPSIS method is utilised to rank each group of the individual, security and privacy factors via the EMR acceptance-based multi-perspective analysis. However, the primary shortcoming of TOPSIS is the lack of provision for weight elicitation and judgment consistency checking. Therefore, TOPSIS requires an effective technique to obtain the relative importance of various criteria with respect to the objective, and AHP provides such a technique. Consequently, AHP is adopted to calculate the weight for the attributes. The most suitable one amongst the recommended MADM/MCDM methods is used to rank the existing alternatives. The integration of TOPSIS (the identified MADM/MCDM method) and AHP is used as basis to apply the proposed algorithm to settle the complexity of the multi-attribute selection issues with various medical records. Figure 4 below shows the steps of integrated AHP and TOPSIS, more about utilise and steps of AHP and TOPSIS methods are illustrated in next sections.

5.1 Weight measurement using AHP

AHP is a popular method used to set the weights in MCDM [173]. This method is based on paired comparisons to produce ratio scales. The ratio scales are measured through the main eigenvectors, whilst the eigenvalue is used to calculate the consistency index.

Weights are assigned to each perspective when using AHP. Each basic perspective is rated for each factor considered for evaluation. Thereafter, AHP is utilised to derive the ratio scales from pairwise comparisons. Three participants, who direct the IT departments in hospitals and who have over four years of experience, were selected to complete AHP. Three copies of pairwise comparisons with a total of six comparisons amongst all perspectives were shown to the participants and their responses on these perspectives were obtained. A relative scale (i.e. 1 to 9) was created to measure the differences in the preferences of the participants with regard to the perspectives. Each IT department head critically analyses these perspectives based on their knowledge. Subsequently, the reciprocal matrix is created from pairwise comparisons. Lastly, the eigenvector is computed to provide the relative ranking of the perspectives. The three evaluators were asked to complete the comparisons of the four criteria. The first evaluator rated physicians as slightly important compared with nurses, considered physicians and pharmacists as equally important and slightly favoured physicians over laboratory employees. Figure 4 shows the preferences of the first evaluator.

The first evaluator considered physicians as slightly more important than nurses and slightly favoured physicians over laboratory employees and pharmacists. In the next step, the AHP measurement matrix is processed to obtain the weights according to the evaluator's preference. Table 1 shows the AHP measurement for the weight preference of the first evaluator.

5.1.1 Rank identified using TOPSIS

Lastly, the TOPSIS method is recommended for use because it is extensively adopted for ranking factors and able to rank several alternative and select the proper one [181, 182]. Figure 3 shows that the available alternative scores are ranked in descending order, whilst the most urgent factors are prioritised based on TOPSIS. The aggregate scores merely provide an idea on which factors are more urgent than others. TOPSIS calculates the scores for alternatives that are factors. Thereafter, the best alternative is selected. This technique indicates that the appropriate option offers the longest geometric distance to the negative ideal solution and the shortest geometric distance to the positive ideal solution. This process is illustrated in the following steps.

Step 1: *Step 1: Construct the normalised DM*

This step attempts to transform the various attribute dimensions into nondimensional attributes, thereby allowing for comparison across attributes. Thereafter, the matrix $(x_{ij})_{m*n}$ is normalised from $(x_{ij})_{m*n}$ to the matrix $R = (r_{ij})_{m*n}$ by adopting the normalisation method as follows:

$$r_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^2}$$

A new matrix R results as the following:

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix}$$

Step 2: *Construct the weighted normalised DM*

A set of weights $w = w_1, w_2, w_3, \cdots, w_j, \cdots, w_n$, which was calculated from the AHP method, was introduced to the normalised DM. To construct the weighted matrix, each column from the normalised DM (R) should be multiplied with its related weight w_j.

The resulting matrix can be calculated by multiplying each column from the normalised DM (R) with its associated weight w_j. The new matrix V results are as follows:

$$\mathrm{V} = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \dots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \dots & w_n r_{mn} \end{bmatrix}$$

Step 3: *Determine the negative ideal and ideal solutions*

Table 1 AHP decision matrix

		Matrix				Normalised Matrix						
	Criteria	Physicians	Nurses	Pharmacist	Laboratory employees	Physicians	Nurses	Pharmacist	Laboratory employees	Aggregation	Weight	Consistency must be below 10%
First Evaluators	Physicians	1	5	7	3	0.59	0.68	0.58	0.50	2.36	0.590	
	Nurses	0.2	1	3	1	0.11	0.13	0.25	0.16	0.67	0.168	
	Pharmacists	0.142	0.333	1	1	0.08	0.04	0.08	0.16	0.38	0.095	
	Laboratory employees	0.333	1	1	1	0.19	0.13	0.08	0.16	0.58	0.146	
	Sum	1.675	7.33	12	6						1	0.089

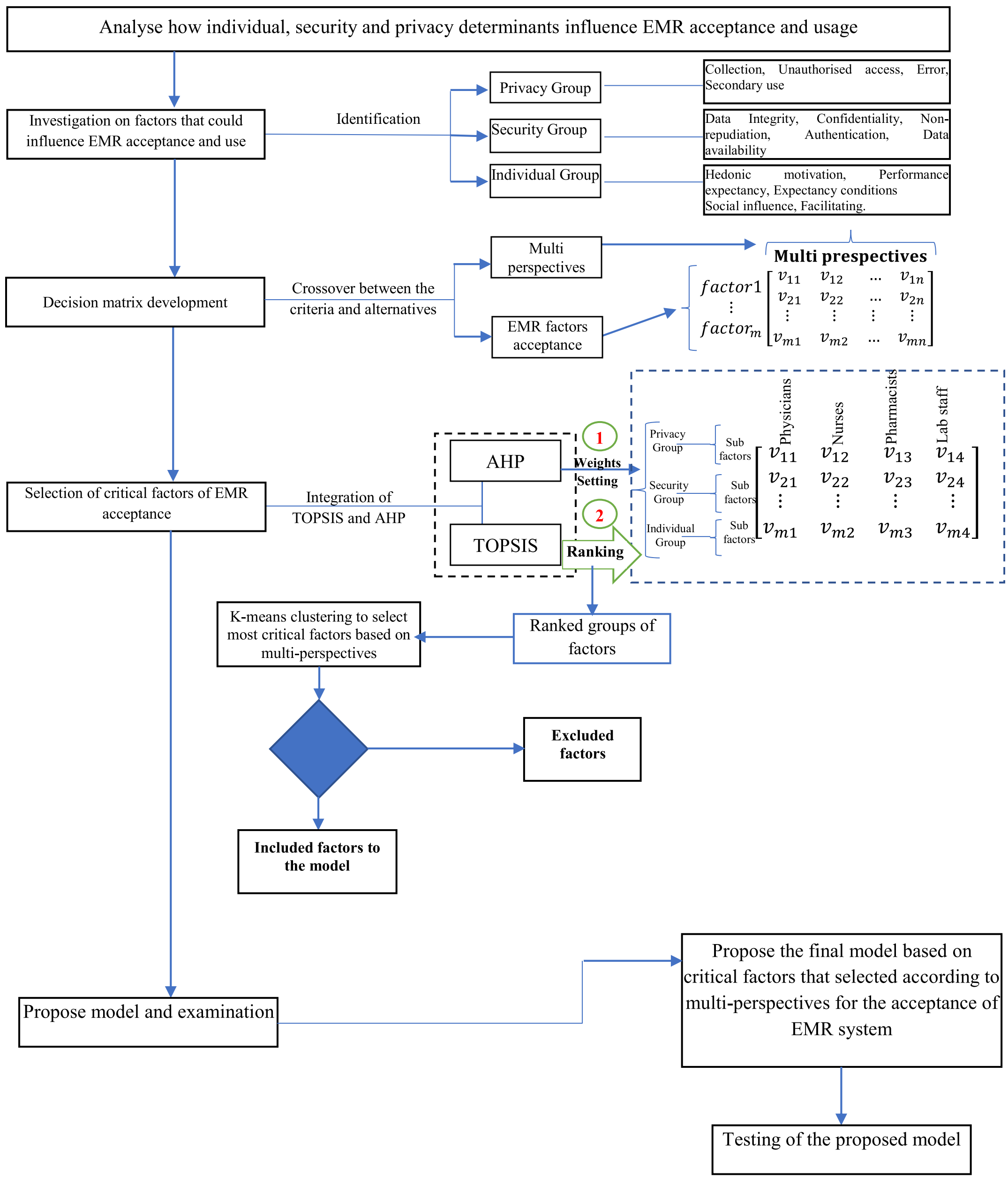

Fig. 3 A new examining framework

A^- (negative ideal alternative) and A^* (ideal alternative) can be calculated as follows:

$$A^* = \left\{ \left(\max_i v_{ij} | j \in J \right), \left(\min_i v_{ij} | j \in J^- \right) | i = 1, 2, \ldots, m \right\} = \left\{ v_1^*, v_2^*, \ldots, v_j^*, \ldots v_n^* \right\};$$

$$A^- = \left\{ \left(\min_i v_{ij} | j \in J \right), \left(\max_i v_{ij} | j \in J^- \right), i = 1|2, \ldots, m \right\} = \left\{ v_1^-, v_2^-, \ldots, v_j^-, \ldots v_n^- \right\};$$

J is a subset of $\{i = 1, 2, \ldots, m\}$, which presents the perspectives (in our case, of the physicians', nurses' and others), whereas J^- is the complement set of J and can be noted as J^c.

Step 4: *Calculate the separation measurement based on the Euclidean distance*

Separation measurement is applied by determining the distance between the ideal vector A^* and each alternative in V by utilising the Euclidean distance as follows:

$$S_{i^*} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^* \right)^2}, \quad i = (1, 2, \ldots m).$$

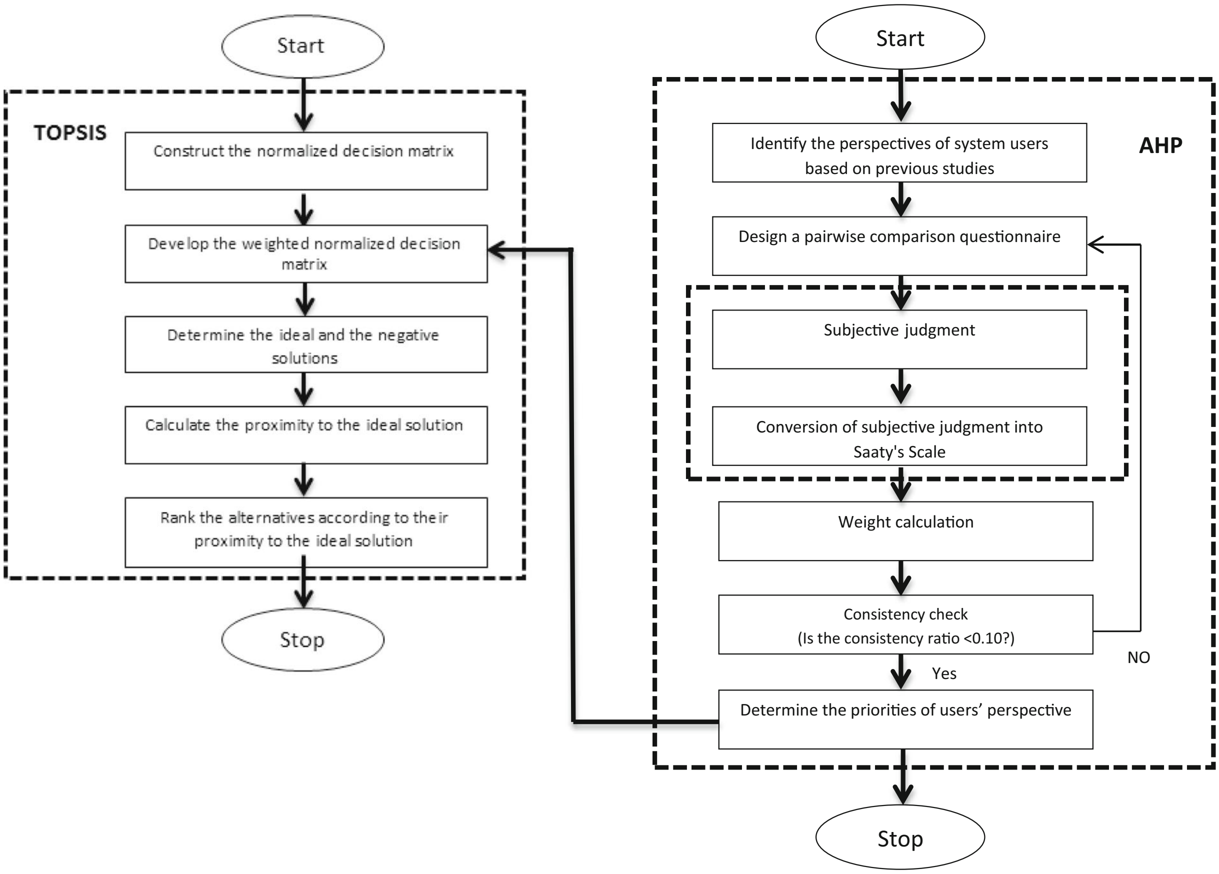

Fig. 4 Integrated AHP and TOPSIS

Similarly, the separation measurement for each alternative in V from the negative ideal A^{-} is given as follows:

$$S_{i^{-}} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^{-}\right)^2}, \quad i = (1, 2, \ldots m).$$

The outcome from this step are S_{i^*} and S_{i^-} for each alternative. These values refer to the distance between each alternative and the two vectors, namely, the ideal and negative ideal.

Step 5: *Calculate the closeness of alternatives to the ideal solution*

The closeness of each alternative (A_i) to the ideal solution A^* is computed as follows:

$$C_{i^*} = S_{i^-}/(S_{i^-} + S_{i^*}), 0 < C_{i^*} < 1 \quad i = (1, 2, \ldots m).$$

Evidently, $C_{i^*} = 1$ if and only if ($A_i = A^*$). Similarly, $C_{i^*} = 0$ if and only if ($A_i = A^-$).

Step 6: *Rank the alternatives*

Lastly, the alternatives can be ranked based on their values. The alternative with the highest value can move forward in the ranking, whereas that with the lowest value can move backward.

5.1.2 K-means clustering

K-means clustering is a type of data classification performed by separating data into groups. This method aims to categorise n objects in k ($k > 1$) groups or clusters using p ($p > 0$) variables. Cluster analysis has several variants, which is similar to many other types of statistical methods. Each of these variants has its own clustering procedure.

K-means clustering is conducted to categorise the outcomes of integrated AHP and TOPSIS into two groups. The group with the high score is considered the critical factors, whereas the other group is excluded from the theoretical model. In this study, K-means clustering is performed using SPSS 22.

5.2 Analysis of the proposed model

We evaluate the factors selected based on the previous step to identify the influence of privacy, security and individual factors on EMR acceptance and use. Moreover, such analysis enhances our knowledge of the factors that affect EMR acceptance and facilitate the enhancement of healthcare professionals' perceptions of EMR acceptance and use.

5.2.1 Population and Sampling

The targeted population of the present study includes EMR system users, such as physicians, nurses, pharmacists and laboratory employees, who work in public hospitals. In 2009, the Ministry of Health mentioned that the five public hospitals had13,000 employees. The sample size is determined based on the formula provided in [183] and the sampling table from [184]. The sample size includes 375 respondents. Data collection was conducted between March and June 2016.

5.2.2 Instrument

A questionnaire was adopted for data collection. A five-point Likert scale was applied to assess the questions. The scale ranged from 1 (strongly disagree) to 5 (strongly agree). Table 2 presents the number of items and values of Cronbach's alpha of the pilot study.

Table 2 Instrument

Variables	Number of items	Cronbach's alpha of the pilot study ($N = 100$)	Cronbach's alpha
Behavioural Intention to use EMR (INTENTION)	4	100	0.738
Data Integrity (DATA)	5	100	0.849
Confidentiality (CNF)	4	100	0.739
Non-Repudiation (NRP)	5	100	0.757
Authentication (AUT)	4	100	0.863
Availability (AVAIL)	4	100	0.903
Unauthorisation (UNAU)	3	100	0.877
Collection (COL)	4	100	0.824
Error (ERR)	4	100	0.878
Secondary Use (SCU)	4	100	0.852
Facilitating Conditions (FCC)	5	100	0.938
Performance Expectancy (PRE)	4	100	0.902
Effort Expectancy (EFE)	5	100	0.898
Habit (HBT)	4	100	0.933
Social influence (SOCI)	5	100	0.830
Hedonic Motivation (HEDO)	4	100	0.933

5.2.3 Data collection

A total of 550 questionnaires were distributed to the respondents for the field study. Data collection was conducted between September 2015 and January 2016. Moreover, the data collection was divided into two phases. The first phase (i.e. pilot study) included a reliability test and selection of the critical factors based on multi-perspectives. A total of 100 questionnaires were distributed to the respondents as follows: 20 questionnaires for each hospital (5 physicians, 5 nurses, 5 pharmacists and 5 laboratory employees). The second phase, which used the main questionnaire, involved 450 questionnaires to identify the influence of privacy, security and individual factors on EMR acceptance and use. A total of 363 usable questionnaires were returned. The sample size is considered high because it meets the criteria set by researchers via structural equation modelling (SEM) [185].

5.2.4 SEM

SEM comprises two major stages: (1) measurement model or confirmatory factor analysis (CFA) and (2) structural equation model. CFA is used to identify the links between manifest or observed and latent or unobserved variables. Therefore, the measurement model can define the manner in which latent or unobserved variables are assessed in terms of the manifest variables [186]. [187, 188] suggested that individual CFA was performed on each of the constructs followed by the measurement model of the study, which provided results and evaluations based on the goodness-of-fit (GOF) indices and evidence of construct validity. The current study employed the maximum likelihood estimation (MLE) as the extraction technique. MLE is one of the most widely used estimation methods that allow testing of individual direct effects and error term correlation.

Stage 1 of SEM: CFA The constructs should be operationalised to ensure accuracy [187, 188]. Several established scales are available for researchers who endeavour to guarantee theoretical accuracy. Regardless of the variety of options, scholars are often hindered by the lack of established scales. Thus, they are compelled to either construct new measurement scales or perform substantial modifications on current scales to conciliate new context. The current study includes three individual CFA models because three second-order constructs are present: security factors (SCF), privacy factors (PRF) and individual factors (INF). Two overall measurement models are also applied to correspond to the two research models in this research.

Stage 2 of SEM: Structural Model The second important process in SEM is the structural equation model. Upon validation of the measurement model, the relationships amongst various constructs should be specified. The various connections amongst different variables can be represented clearly by the structural model. This model can provide details of all the types of included variables [186–188]. The evaluation process of the structural model aims to verify the overall fit of the model and the appropriateness of the hypothesised parameter by estimating the size, direction and significance [187, 188]. The structural model confirmation is the last step in this process. Particularly, this step aims to confirm the fitness of the model built based on the proposed relationship between the identified and assessed variables.

6 Results and discussion

Multi-perspective principles were used to select the critical factors from the three groups based on high weight. The discussion results and evaluation are based on three main steps, namely, decision matrix, factor selection and examination framework.

Step 1: Decision Matrix

The perspectives of users and groups of factors are collected in Step 1, where the four main perspectives are gathered in one platform. The evaluation results for all perspectives are listed in the decision matrix, where the mean score value of the perspective for each factor is calculated (see Table 3).

Table 3 presents the final results of the 15 factors based on the perspectives of physicians, nurses, pharmacists and laboratory employees. This constructed matrix (4 × 15) represents the decision matrix.

Step 2: Factor Selection

The values for the evaluation metrics for the perspectives of physicians, nurses, pharmacists and laboratory staff are presented in Step 2. The factors are classified into three groups, namely, security, privacy and individual factors. The sub-factors in each group are AUT, NON, CON, DATA and AVAIL for the security group; COL, SCU, UNAU and ERR for the privacy group and EFF, PRE, SOCI, FCC, HEDO and HBT for the individual group. The experiment is based on the evaluation metrics of the integrated AHP–TOPSIS. The scores assigned to the weight of perspectives from the three developers (head of IT department) are categorised as W1, W2 and W3 and shown under 'Scores with Different Developer Weighted' (see Table 4).

Table 4 presents the average of each sub-factor and the ranking of each factor within each group, thereby leading to the classification of each group into two clusters, namely, high and low scores. The algorithm of the k-means clustering was applied to arrange factors based on the criterion/features into the *K* numeral of clusters. The value of *K* in this study is equal to two, whereby *K* is a positive integer. Clustering is performed by minimising the sum of the squares of the distances between data and the corresponding cluster centroid. Thus, k-means clustering groups factors into two. SPSS 20 was used to derive the k-means clustering. Table 5 shows the outcome of the k-means clustering.

Table 5 presents the averages of the ranking scores of the three groups based on the different perspectives of users of the EMR system. The results also indicate that the first group (i.e. security factors, including AUT, NON, CON and DATA) belongs to Cluster 2, which is the high score. However, AVAIL belongs to Cluster 1, which is the low score. In the second group, privacy factors, including SCU, UNAU and ERR, are

Table 3 Decision matrix results

Criteria Factors	Physician perspectives	Nurse perspectives	Pharmacist perspectives	Laboratory staff perspectives
AUT	3.38	4.03	3.96	4.1
NON	3.496	3.984	3.896	3.888
CON	3.55	3.93	3.76	3.85
DATA	3.472	4.016	3.85	3.88
AVAIL	3.21	3.86	3.9	4.3
COL	3.49	3.89	3.96	4.2
SCU	3.66	3.98	4.16	4.27
UNAU	3.68	3.813	4.053	4.08
ERR	3.7	3.83	3.89	4
EFF	3.58	3.816	3.76	3.728
PRE	3.53	3.59	4.05	3.75
SOCI	3.13	3.89	3.87	3.98
FCC	3.64	3.408	3.736	3.872
HEDO	3.16	3.89	3.73	3.86
HBT	3.61	3.03	3.36	3.31

Table 4 Scores based on the Integrated AHP–TOPSIS

Groups	Factors	S1+	S1-	W1	S1+	S1-	W2	S1+	S1-	W3	Average	Ranking
Security factors	AUT	0.0142	0.0135	0.5126	0.0145	0.0137	0.5142	0.014	0.0131	0.5166	0.514	1
	NON	0.0223	0.0079	0.7384	0.023	0.0063	0.785	0.0207	0.0108	0.6571	0.726	2
	CON	0.0262	0.0079	0.7683	0.027	0.0065	0.806	0.0243	0.0113	0.6826	0.752	4
	DATA	0.0204	0.0092	0.6892	0.021	0.008	0.7241	0.019	0.0118	0.6169	0.676	3
	AVAIL	5.5539	6.9717	0.0738	3.1849	7.3619	0.0415	1.2441	6.0025	0.1717	0.095	5
Privacy factors	COL	0.0042	0.0291	0.1261	0.0042	0.0357	0.1053	0.0039	0.0305	0.1134	0.114	4
	SCU	0.026	0.0078	0.7692	0.0288	0.0101	0.7404	0.0281	0.007	0.8006	0.770	1
	UNAU	0.0263	0.0107	0.7108	0.0343	0.0106	0.7639	0.028	0.01	0.7368	0.737	2
	ERR	0.0237	0.0083	0.7406	0.0247	0.0136	0.6449	0.0262	0.0067	0.7964	0.727	3
Individual factors	EFF	0.0275	0.01	0.7333	0.0262	0.0111	0.7024	0.0282	0.0095	0.748	0.727	2
	PRE	0.0257	0.0111	0.6984	0.0273	0.0108	0.7165	0.0264	0.0107	0.7116	0.708	4
	SOCI	8.0E-4	0.0357	0.0219	6.0E-4	0.0363	0.0163	8.0E-4	0.036	0.0217	0.019	6
	FCC	0.0326	0.0088	0.7874	0.0328	0.0085	0.7942	0.0334	0.0083	0.801	0.794	1
	HEDO	4.1729	9.2285	0.0433	4.4009	9.15480	0.0459	4.5680	9.2244	0.0472	0.045	5
	HBT	5.3369	2.0314	0.7243	4.7914	2.3498	0.671	6.1234	1.7576	0.777	0.724	3

categorised under Cluster 2, whilst COL belonged to Cluster 1. In the last group, the individual factors, including EFF, PRE, FCC and HBT, are grouped in Cluster 2, whilst SOCI and HEDO are considered in Cluster 1. Thus, AVAIL, COL, SOCI and HEDO acquire low scores. Consequently, H1c, H1e, H2e and H3b are excluded from the conceptual model. Factors with the highest scores are considered critical factors.

Step 3: Examination of the Conceptual Model

The conceptual model is analysed using the AMOS software. The two stages of examination are CFA and structural model.

Table 5 K-means Clustering

Groups	Case Number	Factor	Cluster	Distance
Security group	1	AUT	1	0.153
	2	NON	1	0.059
	3	CON	1	0.085
	4	DATA	1	0.009
	5	AVAIL	2	0.000
Privacy group	1	COL	2	0.053
	2	SCU	1	0.083
	3	UNAU	1	0.003
	4	ERR	1	0.046
Individual group	1	EFF	1	0.020
	2	PRE	1	0.054
	3	SOCI	2	0.084
	4	FCC	1	0.033
	5	HEDO	2	0.058
	6	HBT	1	0.035

6.1 Stage 1 of SEM: Overall CFA model for the research model

For the research model, CFA is used to analyse the overall measurement model. The overall measurement model includes all latent constructs with their corresponding indicators. Figure 5 presents the overall CFA model for the second research model (Fig. 7).

6.1.1 Goodness of Fit Indices

The results show that the overall measurement model for the research provides adequate fit of data (Chi-square = 1386.527, df = 1158, p value = 0.000, GFI = 0.874, AGFI = 0.855, CFI = 0.962, TLI = 0.980, IFI = 0.982, RMSEA = 0.023 and Chi-square/df = 1.197).

6.2 Stage 2 of SEM: Structural model for the research model

The various direct effects of the different independent variables are analysed using the structural model. These variables are PRE, EFE, FCC, HBT, AUT, DATA, CNF, NRP, UNAU, SCU and ERR on INTENTION, which is the dependent variable. The 11 effects pertain to H1a, H1b, H1d, H1f, H2a, H2b, H2c, H2d, H3a, H3c and H3d, respectively.

6.2.1 Direct effects of the variables

Figure 8 presents the hypothesised effects test with standardised regression weights using AMOS.

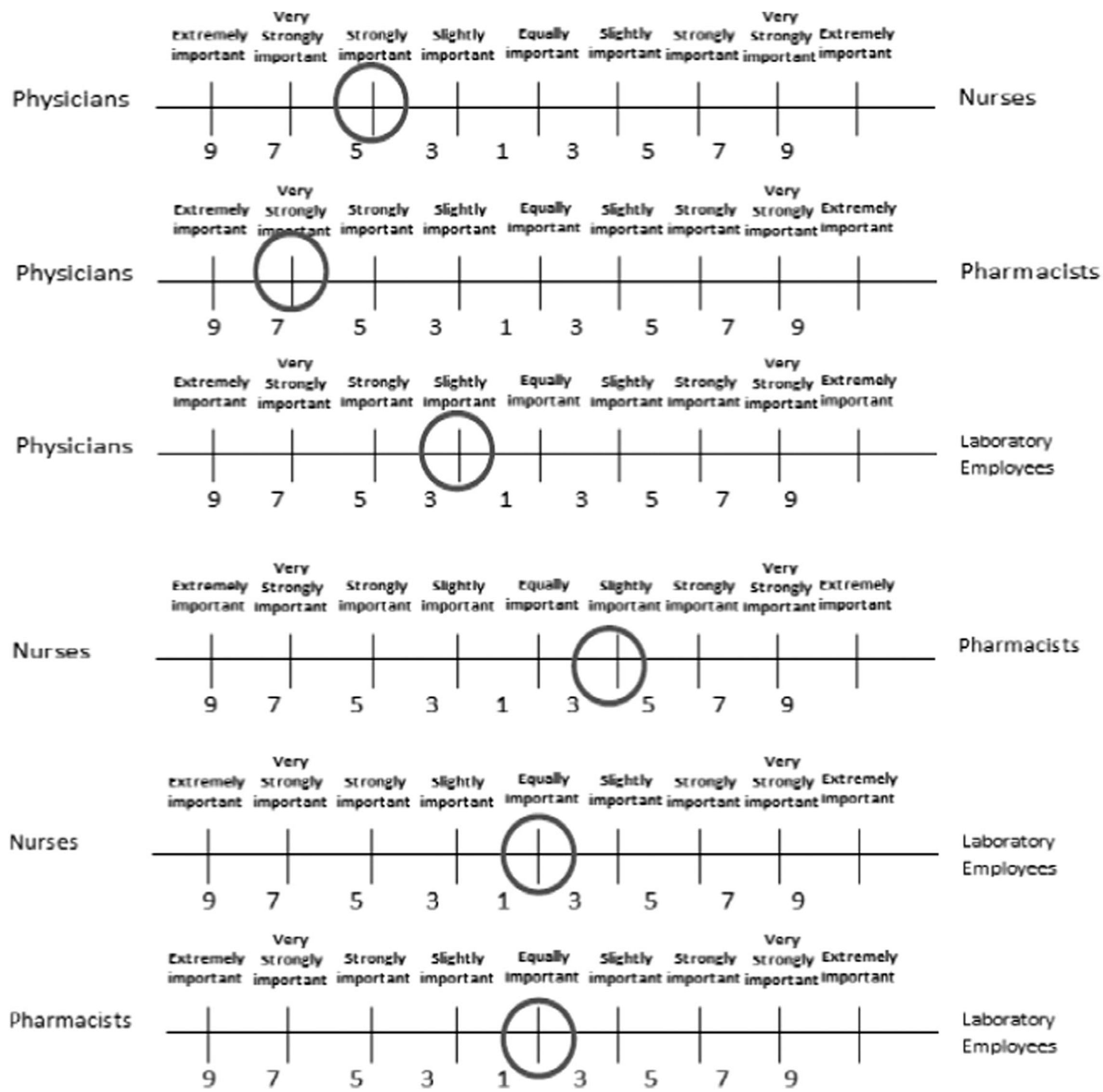

Fig. 5 Pairwise Answers from the first evaluator

The GOF indices show that the structural model is adequately fit for the data: RMSEA = 0.023, GFI = 0.874, AGFI = 0.855, df = 1158, $p = 0.000$, $\chi2 = 1386.527$, CFI = 0.982, TLI = 0.980, IFI = 0.982 and $\chi2/\mathrm{df} = 1.197$.

Although the chi-square is statistically significant, this outcome is not considered unusual given the large sample size involved in this study [187, 188]. The value of R^2 for INTENTION is 0.57, which satisfies the cut-off value of 0.10 [187, 188]. The coefficient parameter estimates are tested to determine the hypothesised direct effects of the variables.

Table 6 shows that the eight paths, namely, DATA, CNF, NRP, UNAU, ERR, SCU, FCC and EFE, on INTENTION are statistically significant because their corresponding p-values are below 0.05. Thus, the results support H1b, H1d, H2b, H2c, H2d, H3a, H3c and H3d, respectively. By contrast, the effects of AUT, PRE, and HBT on INTENTION are insignificant because their *p*-values are above 0.05. Therefore, H1a, H1f and H2a are rejected.

Security factors The four dimensions of security are data integrity, confidentiality, authentication and nonrepudiation. The overall acceptance and use of EMR is positively related to security. Evidence supports H2, whilst the positive correlation between EMR acceptance and use and security implies the trend of safety consciousness amongst healthcare professionals. The protection of personal information is a strong driving force for developing security policies. Healthcare organisations should consider analysing and assuring security policies in responding to issues and formulating policies that protect medical information. Similar results are obtained in other research [110, 189, 190]. [191] used SSA countries as population and reported the significant and positive effects of security in the adoption of telemedicine. [192] showed that

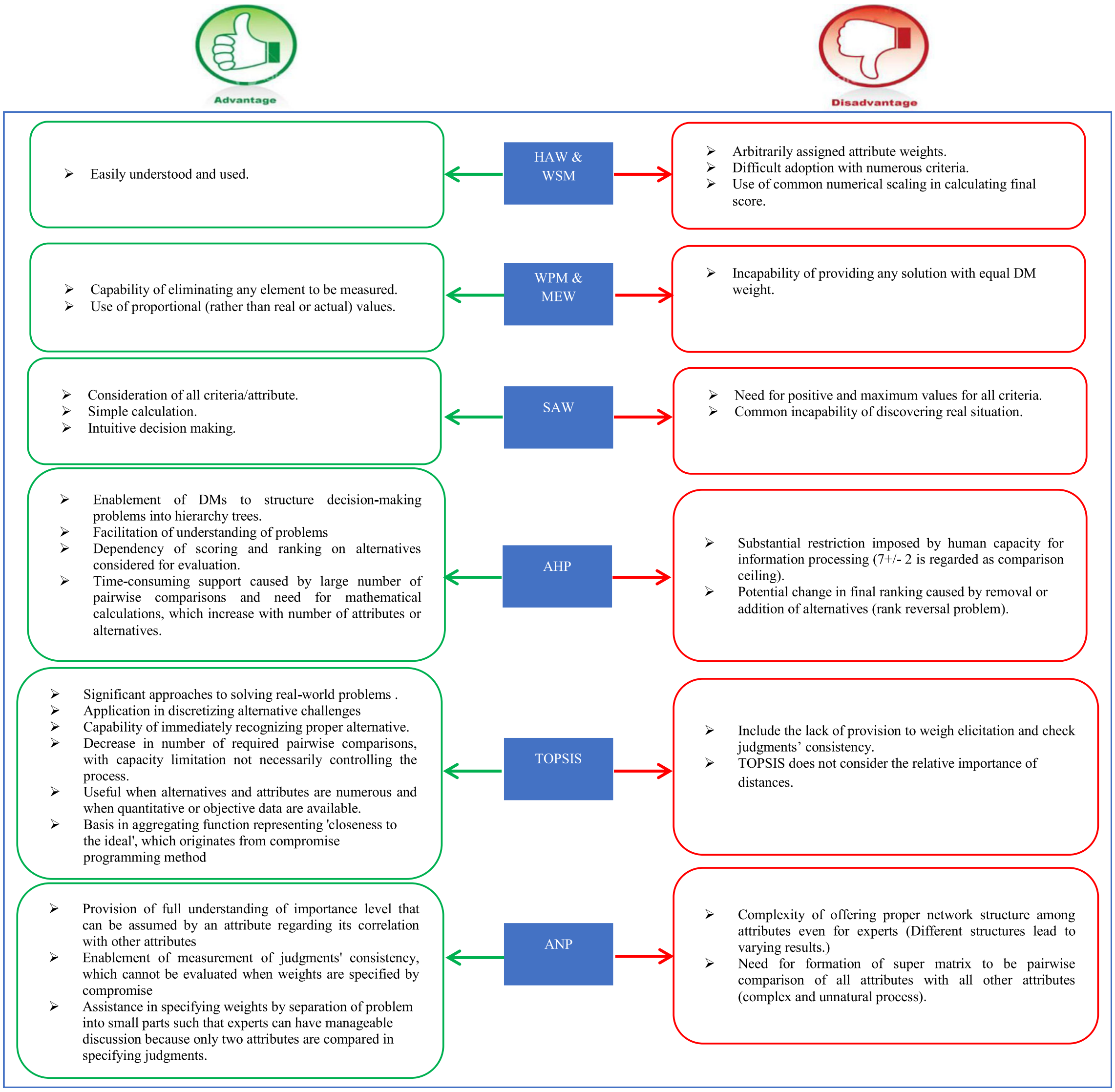

Fig. 6 Advantages and disadvantages of the MCDM methods

safety effects exert significant and positive effects on telemedicine usage. [193] claimed that an important and positive relationship exists between security and the possibility of applying e-commerce. [194] indicated that security directly influences user intent to utilise web-based services. Although evidence may propose that security affects EMR acceptance and use, the effect is different in every security dimension. The research outcomes show that data integrity is related with EMR acceptance and use, thereby supporting H2b. [195] reported similar results, in which the connection between completeness and intent is significant (β = 0.365). [196] also presented that the use of data integrity intentions increases when a system provides accurate and reliable patient data. Lead healthcare professionals use the system to improve the quality of their work and reduce medication errors. The present study determined that confidentiality is related to EMR acceptance and use. Thus, H2c is supported. This result is similar to that in [197], in which the perceived positive effect of confidentiality has a high probability of being adopted. [198] determined that security and confidentiality issues and system risk in e-commerce are major factors of adoption behaviour. Therefore, confidentiality positively affects EMR acceptance and use. Moreover, confidentiality ensures that only authorised healthcare professionals have access to patient data. Thus, H2d is supported. That is, no one can refuse to receive or send records. [199] demonstrated that nonrepudiation exerts a significant positive effect on user intention. However, H2a is unsupported. This result is similar to that in [200], in which authentication was determined to have no effect on the majority of the key factors related to online banking adoption.

Privacy factors Privacy comprises collection, secondary use, unauthorisation and error. Overall, EMR acceptance and use

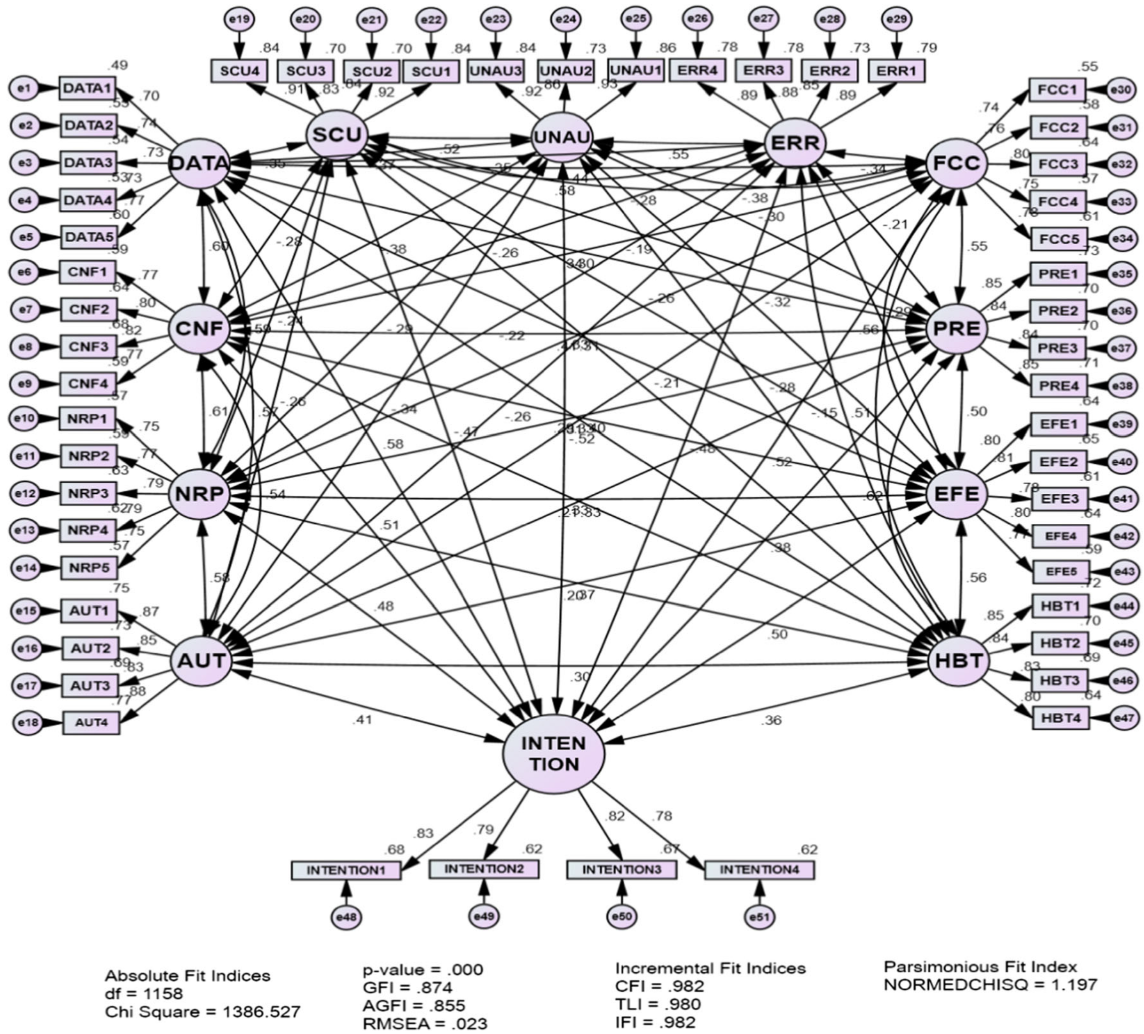

Fig. 7 Overall CFA Model for the Research Model 2

are negatively associated with privacy concerns. Thus, H3 is supported. The negative association between EMR acceptance and use and CFIP shows a trend in privacy concern amongst healthcare professionals. Thus, high privacy concerns result in low acceptance and use of EMR systems amongst healthcare professionals. Similar to [148], CFIP and LOA indicate a highly significant negative relationship (βCFIP = −0.12, $p < 0.05$). Moreover, [148, 201, 202] tested various relationships between privacy concerns and intentions and reported mixed results. [203] provided empirical evidence propping the direct relationship between privacy challenges and behavioural intentions, claiming that the opt-in for EHR is low when privacy issues are high. Hence, H3a is supported. The results show that when non-medical treatment exerts a negative impact on EMR acceptance and use through healthcare experts, electronic medical records are used to treat patients, whilst medical information should be private and confidential. Doctors maintain the importance of maintaining the safety of patient data. Otherwise, legal issues may arise when unauthorised users enter the system. Additionally, improper disclosure of patient information can add to legal woes. Evidently, doctors are more concerned about this issue than the patient. Security breach threatens privacy of information in medical facilities; insiders may access data without proper authority through technical or other means [204]. Consequently, healthcare professionals care about patient information. Thus, H3d is supported. Errors in medical data records can affect the health status of patients, particularly if they are prescribed medications that may cause allergic reactions. A study showed that 32% of patients determined errors in their personal medical information upon obtaining their EHRs. The order of medical errors, testing and treatment and the response to reminders are related to the usage of electronic records [205]. Hence, H3c is supported. Secondary use is associated with the acceptance and use of EMR. The increasing concern over privacy issues has basis when the organisation processes more data than primary exchange. Additionally, the unauthorised use of personal information for other purposes often results in negative personal reactions [148]. With EMRs in place, physicians are concerned with

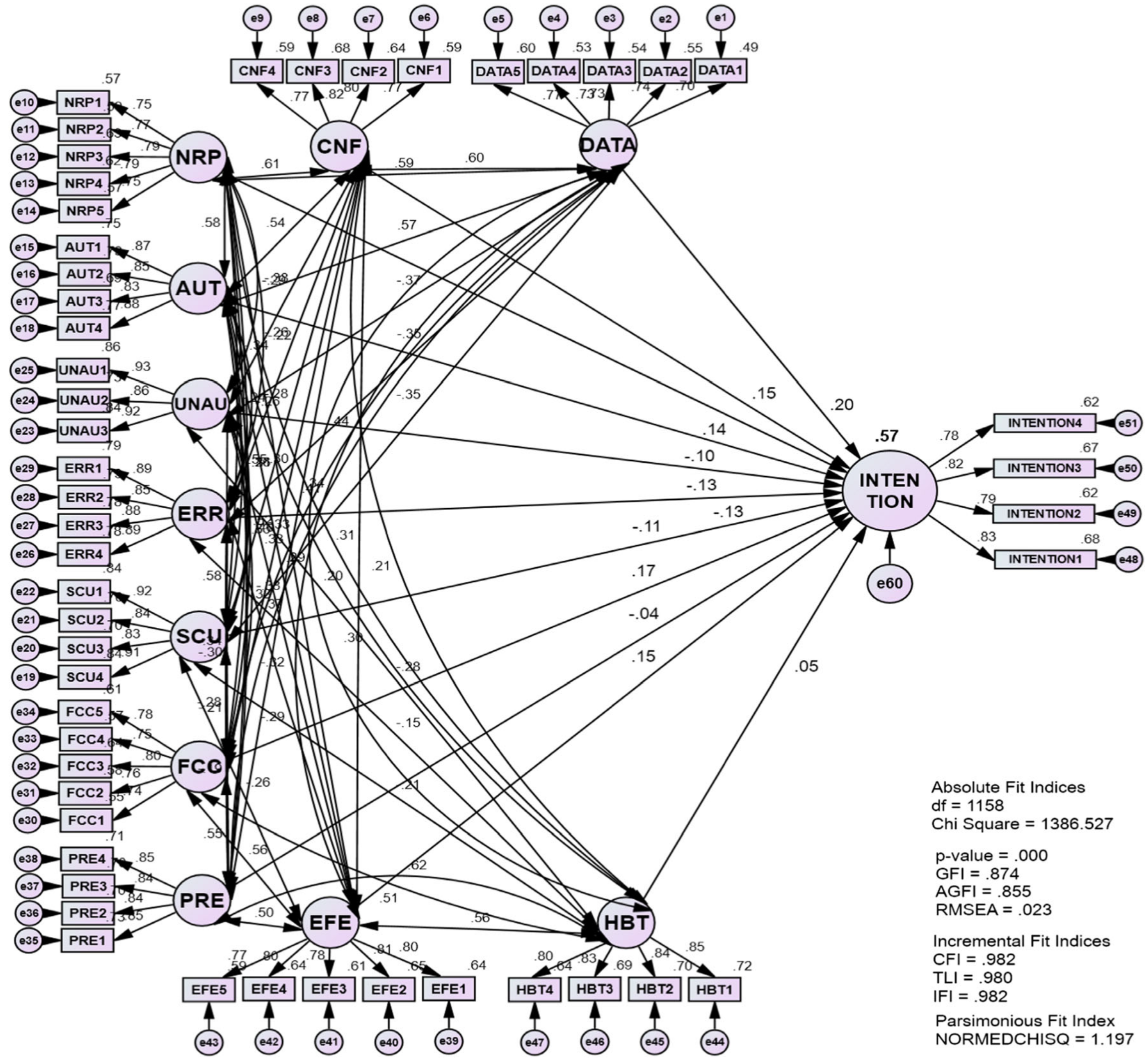

Fig. 8 AMOS graph of the structural model

Table 6 Direct effect results

Path	Unstandardized Estimate		Standardized Estimate	c.r.	P value	Hypothesis Result
	Estimate	S.E.	Beta			
PRE → INTENTION	−0.04	0.069	−0.037	−0.586	0.558	H1a—Rejected
EFE → INTENTION	0.178	0.075	0.148*	2.37	0.018	H1b—Supported
FCC → INTENTION	0.194	0.076	0.166**	2.566	0.01	H1d—Supported
HBT → INTENTION	0.064	0.082	0.05	0.755	0.438	H1f—Rejected
AUT → INTENTION	−0.095	0.058	−0.1	−1.646	0.1	H2a—Rejected
DATA→INTENTION	0.278	0.102	0.196**	2.727	0.006	H2b—Supported
CNF → INTENTION	0.179	0.082	0.147*	2.18	0.029	H2c—Supported
NRP → INTENTION	0.177	0.083	0.143*	2.12	0.034	H2d—Supported
UNAU→INTENTION	−0.1	0.044	−0.134*	−2.303	0.021	H3a—Supported
SCU → INTENTION	−0.092	0.047	−0.111*	−1.961	0.05	H3c—Supported
ERR→INTENTION	−0.109	0.049	−0.135*	−2.25	0.024	H3d—Supported

*$p < 0.05$, **$p < 0.01$, ***$p < 0/001$

losing control of patient information and work processes. Hence, data can be shared and evaluated by others. [206] claimed that doctors' perception of the threat of their expert autonomy is a necessary response to EMR.

Individual factors The use of our research model in a health-related area with the EMR acceptance and use of healthcare professionals yields good results. The proposed model explains 60% and 57% of the variance on behavioural intention for Models 1 and 2, respectively. The most important contributors that indicate significant effect on behavioural intentions are the effort to anticipate and promote conditions. Thus, H1b and H1d are supported. [99] proposed that users with better conditions to use e-health technologies favoured the adoption of e-health services. Other studies, such as [98], have reported that facilitating conditions have a positive effect on physician-based clinical decision support systems for physician-based behavioural pharmacokinetics. Moreover, life expectancy has a significant positive effect on the intention to use clinical decision support [98], healthcare information [100] and adverse event reporting systems [101]. However, H1a and H1f are not supported by performance expectations and habits. Performance expectations have no significant effect on behavioural intent as demonstrated by the original study on UTAUT [82] and similar studies on technology acceptance and use [55, 207–209]. [88] Explained that 'habit ($\beta = 0.019$, $p > 0.01$) has no positive effect on behavioral intention or LMS use behavior'.

Overall, the effects of DATA, CNF, NRP, UNAU, ERR, SCU, FCC and EFE on INTENTION are statistically significant because their *p*-values are below the standard significance level of 0.05. Hence, H1b, H1d, H2b, H2c, H2d, H3a, H3c and H3d are supported. Conversely, the effects of AUT, PRE and HBT on INTENTION are insignificant because their p-values were above 0.05. Thus, H1a, H1f and H2a are rejected.

7 Contributions

7.1 Theoretical contribution

Firstly, the results of this study are utilised to facilitate the theoretical contributions. The limited literature on EMR, particularly in Malaysia, makes the present study an important source of knowledge for EMR acceptance. UTAUT2 is applied to explain the behaviour of healthcare professionals, thereby improving the understanding on fit of theory in EMR acceptance. Data collected from various perspectives based on EMR users present additional contribution to the related literature. The present study emphasises the role of external forces in mediating the positive effects of privacy and security on healthcare professionals who receive EMR. Additionally, a theory is proposed by analysing the effect of privacy and safety factors on EMR acceptance. This finding can assist hospitals in recognising and utilising factors that reflect full acceptance and use of EMR systems, thereby possibly influencing EMR acceptance.

7.2 Methodological contribution

Analysis of the data indicates the considerable reliability and robustness of the findings compared with other analyses in prior studies. The current research also contributes to the quantitative format by studying the impact of privacy and security on EMR acceptance and use that are obtained based on the multiple perspectives of EMR users. This study combines two approaches (i.e. quantitative approach and MCDM) to analyse and determine the key factors based on multiple perspectives that can improve the understanding on privacy and security issues from various perspectives. Moreover, responding to each point of view is crucial because each factor has a variety of perspectives. The current study also presents a new decision matrix that resulted from considering various perspectives and groups. This study uses the AMOS software to validate data.

7.3 Practical contribution

Malaysia seeks to improve the acceptance and use of EMR systems through enhanced privacy and security. Therefore, the security and privacy results on EMR systems of this study are applicable in addressing such a need. The practical aspect of this study shows a good representation of the present privacy and security situation in EMR acceptance and use. The results can benefit other sectors, such as car dealers, because they can influence their comprehension of current practices. The results can encourage other healthcare professionals to encourage the acceptance and utilisation of EMR systems. This study highlights the necessity of privacy and security measures and enhances the confidence of current and potential healthcare professionals. A considerable analysis of the privacy and security issues from the side of healthcare professionals will lead to acceptance and usage of EMR systems. The current study indicates that the EMR system can minimise medication errors, improve quality of care and service to patients and reduce time in dealing with patients. Malaysian hospitals can benefit from the implementation of EMR systems. In this study, healthcare professionals assessed their actions based on their acceptance and use of EMR systems. The results can serve as reference for hospitals to improve their existing healthcare professional practices. Thus, hospitals can explore investment opportunities and become internationally competitive by increasing their competitive advantage. Moreover, the findings of this work show that the EMR system could be applied in other industries.

7.4 Policy contribution

The empirical evidence of EMR acceptance practices amongst healthcare professionals in Malaysia provide a good representation of existing healthcare-related organisations. The positive association amongst privacy, security, EMR acceptance and use enables this study to guide other healthcare professionals to accept and use EMRs. Government offices, such as the Ministry of Health (MOH), public and private hospitals and developers of EMR systems may find this study beneficial, particularly on how the implementation of privacy and security can further enhance EMR acceptance and use.

8 Limitations

This study only considers a single medical system. Therefore, conclusions are based on a single sample and may not be generalised to certain populations, thereby possibly leading to inaccurate description of attitudes. Additionally, geographical divisions in Malaysia may affect the perception of EMR. People living in various geographical locations are expected to show varied attitudes. Another limitation of this research is the use of generic surveys in data collection. Although surveys are important in obtaining quantitative data, they are not conducive to in-depth study and investigation of specific problems. The small sample size is also a limitation because only a few individuals agreed to participate in our study. The present study is limited to two major Malaysian healthcare facilities. Thus, future research should consider the inclusion of other middle and small healthcare facilities and other neighbouring countries. Furthermore, EMR implementations are concentrated on general EMRs and not on any particular type. Future researchers can investigate properties, advantages and issues connected to other EMR software packages. Lastly, different levels of healthcare professionals use EMR. However, only four groups of health professionals are considered in this study. Therefore, other settings and sample groups are needed in medical record staff replication to improve the understanding of how such findings can be generalised. User perception can evolve over time because individuals acquire additional experience and exposure. The repetition of the study facilitates the stabilisation of the notion of healthcare professionals on using EMRs.

9 Future research directions

This study focuses on the user population of a few medical systems. Future research can consider the outcome of the present study and apply the findings to large groups. User interviews and observations will provide a clear and comprehensive idea of the needs of medical professionals. Moreover, other areas of study can include specific user groups in a healthcare system, such as other healthcare professionals, nurses and administrators. EMR acceptance models can also be evaluated in other areas to determine various attitudes in different settings. Future research can even further apply the research findings to non-academic healthcare professionals and sites. Such a strategy can test EMR utilisation and models in nonmandatory health organisations, such as other hospitals. The majority of the findings from the present research were concerned with the perceptions of healthcare professionals regarding factors that affect the actual system in use. Future research can discuss the study by presenting a pre-implementation usability study for an extensive appreciation of EMRs amongst healthcare professionals or nurses' duties and performance. Furthermore, future studies can perform retrospective research to analyse features that are often used and disregarded. Different professional uses and customised comparisons of document templates are other potential areas of research because perceptions vary based on the profession. The analysis of various uses can uniquely address the issues of other practitioners. For example, future studies can compare the use or templates in data entry formats, such as narrative documentation, digital dictation or data capture through handheld devices. The results of these studies can be used by EMR vendors and healthcare systems that cater to data entry needs. Pre-implementation measures assess the applicability of a system to adopt EMR. However, continuing evaluation programs are necessary to understand the effect of EILIR on users and on patient care.

10 Conclusion

This study empirically analyses EMR acceptance and use in Malaysian public hospitals. The factors that affect EMR acceptance and use are likewise investigated. Four groups of healthcare professionals contribute to this study, namely, physicians, pharmacists, nurses and laboratory employees. The respondents worked in five major Malaysian public hospitals. Success is achieved because the research objectives are met. The goal of this research is to investigate the factors that influence EMR acceptance and use in Malaysian public hospitals and develop a study model. To achieve these research objectives, the present study extended UTAUT2, which is a popular model that has been validated by considerable statistical analyses. The outcome generated by UTAUT2 can be utilised as statistical evidence for decision makers in including MOH of Malaysia and healthcare organisations in their attempts to develop strategic plans for healthcare professionals and maximise effective EMR acceptance and use. The results can contribute to the knowledge on EMR software developers because the weakness of the software is identified in the present study. Furthermore, this study contributed to health informatics, particularly to the acceptance and utilisation of electronic patient record in health institutions. Empirical support means that user acceptance factors accepted and used by EMR included security factors (i.e. data integrity, confidentiality and nonrepudiation), individual factors (i.e. facilitating conditions and effort expectation) and other factors, such as unauthorisation and error. Therefore, the replication of these results can further develop UTAUT2.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all participants of the study.

Appendix

Questionnaire

Authentication

EMR ensures that the patients' information I send is transmitted to the right health care staff member, to whom I want to transmit it to.

EMR ensures that the patients' information I receive are transmitted from the right health care staff member, to whom I want to receive it.

EMR ascertains my identity before sending any patients' information to me.

EMR ascertains my identity before processing patients' information received from me.

Nonrepudiation

EMR ensures that other healthcare staff will not deny having participated in patient information after processing it.

EMR ensures that other healthcare staff will not deny having sent me patient information.

EMR ensures that other healthcare staff will not deny having received patients' information from me.

EMR ensures that other healthcare staff provide me some evidence to protect from the denial of having sent the patient information.

EMR ensures that other healthcare staff provides me some evidence to protect from the denial of having received the patient information.

Confidentiality

EMR ensures that all communications of EMR system are restricted to all authorized healthcare staff.

I am convinced that the received information will be treated with respect and confidentiality by other healthcare staff.

EMR uses some security controls (e.g. firewall) for the confidentiality of patient information.

EMR checks all communications between me and the other healthcare staff are protected against wiretapping or eavesdropping.

Data Integrity

EMR checks the patient's information communicated with me for accuracy.

EMR takes steps to make sure that the transmission of the patient information is accurate.

EMR takes steps to make sure that the transmitted information of the patient information is not deleted.

EMR devotes time and effort to verify the accuracy of the patient information in transit process.

EMR system devotes time and effort to verify that the patient information in transit process is not deleted or tampered.

Availability

The probability of patient information system breakdown and information service disruption in my hospital is low.

A legitimate user with medical needs can access hospital patient information at any time and place.

The hospital ensures that a backup exists to tolerate hardware failure.

All servers should be continuously available to patients.

Trust

The hospital's EMR system is trustworthy.

I trust in the benefits that came from the hospital's EMR.

The hospital's EMR system keeps its promises.

The hospital's EMR keeps health care staff's best interests in mind.

Even if not monitored I would trust the hospital EMR system to do job right.

I would use EMR than the traditional way of collecting patients' information.

Implementing EMR system is the right policy of the hospital.

Collection

It usually bothers me when hospital asks for patient information.

When hospital asks patients for personal information, I sometimes think twice before recording it.

It bothers to give the patients' information to other health care companies.

I'm concerned that hospital is collecting excessive information about patients.

Secondary use

A hospital should not use patient information for any purpose unless it has been authorised by the patient who provided the information.

When a patient gives personal information to a hospital for a particular reason, the hospital should never use that information for any other reason.

Hospital should never sell any of the patient information to third party.

Hospital should never share the patient information with other companies unless they gain approval from the patients to do so.

Unauthorised access

Hospital should devote additional time and effort to prevent unauthorised access to personal information.

Computer databases that contain patient information should be protected from unauthorised access – no matter how much it costs.

Hospital should take more steps to make sure that unauthorised people cannot access any of the patient information in its computers.

Error

All the patient information in computer databases should be verified for accuracy—no matter how much this costs.

Hospital should take additional steps to make sure that the information in the patients' files is accurate.

Hospital should have improved procedures to correct errors in patient information.

Hospital should devote additional time and effort to verifying the accuracy of the patient information in its databases.

Effort Expectancy

The EMR can be used easily.

Learning to use the EMR is easy.

The process for using EMR is clear.

Using EMR system is not burden during the transition.

The hospital is self-solving when an error occurs.

Performance Expectancy

EMR accelerates the healthcare process.

The EMR enhances staff's performance.

The EMR enhances the efficiency of your service.

The EMR enhances the accessibility and communication with the patient.

Social Influence

Your colleagues expect that your service improves via EMR system.

Your colleagues expect that you can use the EMR system efficiently.

The patient believes that the EMR system is very useful for your organisation.

The hospital supports training and attending seminars to increase their knowledge of EMR.

Facilitating Conditions

The hospital gives importance to service driven by EMR technology.

The hospital always improves and upgrades their EMR.

The hospital provides me with the required tools to use EMR.

The hospital supports training for new staff by a professional trainer.

The hospital provides the training for healthcare professionals whenever there is important system/technology.

Hedonic Motivation

Using EMR system makes your job fun.

Using EMR system makes your job enjoyable.

Using EMR system is very entertaining.

Time passes fast when using EMR system.

Habit

The use of EMR system has become a habit for me.

I always use EMR system.

I must use EMR system.

Using EMR has become natural to me.

Behavioural Intention

I want to use new technology to serve the patients.

I intend to continue using EMR system in the future.

I will try to use EMR system in my daily life.

I plan to continue using EMR system frequently.

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