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Research article

Perspectives to social media usage of depressed patients and caregivers affecting to change the health behavior of patients in terms of information and perceived privacy risks

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ABSTRACT

It has been confirmed that the use of social media (SM) can affect the mental health of users. However, there is no explanation for its impact on health behavior. This study focuses on the perspectives of depressed patients and caregivers on social media usage and how it can change their health behavior. A questionnaire designed according to the framework of the I-Change Model (ICM) is used to collect data from a sample group. This group consists of 214 patients diagnosed with major depressive disorders, and 110 caregivers. The data is used to analyze causal relationships with the help of structural equation modeling. The results showed that from the patient's perspective it is essential to be aware of the content and volume of social media usage. An awareness of the perceived risk to privacy is also essentially a motivating factor in patients' decisions to use social media. The views of caregivers suggest that content valence has an essential role to play in their use of social media. After viewing content on social media patients change their behavior. The perceived privacy risk also plays a critical role in patients' decisions to use social media.

1. Introduction

One of the psychiatric disorders that are the most public health problems is depressive disorder (WHO, 2017). According to the World Health Organization report, it also found that the leading cause of the loss of health of the world population is caused by depression which can predict that health loss is the second only to cardiovascular disease in 2020 (WHO, 2017). In addition, the severity of the symptoms also harms the idea of the suicide of patients (Angst et al., 1999; Gaynes et al., 2004; Stoudemire et al., 1986). According to the Department of Mental Health of Thailand, Considering the number of Years Lost due to Disability (YLD) was found that depression was the first leading cause of loss in Thai females and the second in Thai males.

There are many factors causing depressive disorders. Biopsychosocial models are therefore employed in this study to investigate the factors related to depressive symptoms (Engel, 1980). These can be divided into three main groups: 1) biological factors causing neurotransmitter disorders and genetic disorders (aan het Rot et al., 2009; Shyn and Hamilton, 2010); 2) psychological factors causing personality disorders or abnormal behavior; and 3) social factors related to the social and environmental conditions in which people live. Previous research has found social media (Facebook, Instagram, Twitter, and YouTube) to be a key factor affecting the mental and social well-being of people (Banjanin et al., 2015).

The popularity of social media (SM) has increased nowadays. This has resulted in a wide variety of user-generated content in the form of videos, text, images, and audio (Fu et al., 2017). The process of creating and sharing this content has led to the generation of emotional transmission among users (Coviello et al., 2014). It has made scholars aware of the importance of studying the impact of increasing amounts of content. However, the results of most studies have focused on general users who use SM, especially Facebook, and are presented only in the form of descriptive statistics, and cannot explain the relationship between related factors.

Recently, SM studies into users with mental health problems have received increasing attention, especially in the case of depressive patients who are at risk of mental stimulation (Smith et al., 2017) that might lead to suicide problems. These research groups have focused on the study of usage behavior (frequency or quantity) using descriptive statistics (Lin and Utz, 2015; Liu et al., 2017; Park et al., 2016) and risk behaviors (Radovic et al., 2017). Nevertheless, there is no presentation on the

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impact of content on SM, risk, the relationship between factors, and changing behavior that may result in serious suicide attempts.

However, there are researches studied to the process of changing health behaviors using the I-Change Model (Hein de Vries, Mesters, Van de Steeg and Honing, 2005) including sleep behavior (Cassoff et al., 2014), smoking cessation (Rüther et al., 2015), alcohol consumption (van der Wulp et al., 2013). Moreover, some studies confirm that the possibility of lifestyle interventions by using SM is an influence on health behaviors in depressed patients (Jattamart and Leelasantitham, 2019). The results only explain the relationship between factors and intentions, but as yet there have been no studies into the relationship between change health behaviors, content, and the risk of both privacy and unreliability of information on SM.

This research has been designed to fill the gaps in this area by focusing on the perspectives of SM usage in depressed patients and caregivers affecting to change the health behavior of patients in terms of information and perceived privacy risks. This study has done by applying the I-Change Model (ICM) theory in this research. It believed that it is the first time that ICM theory used to explain the behavioral changes of depressed patients. We propose to test the relationship with the involved factors using Structural Equation Modeling (SEM). This can be acted as a guideline for health educators and can be used to prevent disease or stimulate our understanding of the disease. The purpose of the research has been explained by considering the following research questions.

RQ1. Does the information on SM influence awareness concerned with the use of SM on the part of depressed patients?

RQ2. Does awareness of the use of SM on the part of depressed patients influence their motivation to use SM and lead to changes in health behaviors?

RQ3. Does the motivation to use SM on the part of depressed patients influence changes in health behaviors?

RQ4. Does the perceived privacy risk with regard to using SM on the part of depressed patients influence their motivation to use SM and lead to changes in health behaviors?

This article contains the following contents: Part 2 presents the literature and the theoretical framework of SM in terms of health and behavior changes, Part 3 presents information about the research model and the hypotheses that have been developed, before presenting research methods relating to the tools through the use of measuring and evaluating the results presented in Part 4. The results of this research are presented in Part 5, and the research results will be discussed in Part 6. Part 7 will be described for the implication of theories and practices, the limitations, and the future work guidelines before finally presenting the conclusion.

2. Literature and theoretical framework

2.1. Social media content

According to Global Social Media Usage statistics in 2019, there are currently 48 billion SM users (37% of the global population) and 3.26 billion access SM on mobile phones. The most popular SM is Facebook, which has 2,200 million users. Most users are in the 18–24 year and 25–34 year age groups (Kemp, 2019). Content is therefore generated by a large number of users whereas in the early days of the Internet content was created by website owners who were the messengers while the users were merely recipients (Fu et al., 2017).

In terms of online business, the use of SM is a marketing technique that has used to promote sales by reaching more consumer groups, attracting the target group so that they are impressed by and remember products, and recognizing the direct needs of consumers (Moe and Schweidel, 2017). The specifics nature of marketing on SM is that it facilitates two-way communication between businesses and consumers (peer to peer) (Fu et al., 2017). Consumers can create content, also known as "User-Generated Content UGC)", and disseminate this via electronic word-of-mouth (e-WOM) experience that is an integral part of sharing information on SM (C. S. Lee and Ma, 2012). It is a vast source of information that affects business and consumer trust (Chan and Ngai, 2011; Yen and Tang, 2019) and thus differs from traditional marketing where the organization or business is the creator of official content.

An issue arises about users creating and sharing their content concerned with its quality and reliability (Figueiredo et al., 2013). Readers would be expected to benefit from valuable content as previous studies have shown that, from a business perspective, the reliability of the information shared helps promote corporate marketing (Osatuyi, 2013). The views of users also has reported that that the reliability of information and the influence of other users affects the sharing of user information (Zhang, Moe and Schweidel, 2017). Based on the content of marketing promotions, Peters et al. (2013) are grouped into content from a literature review into three key aspects: 1) content quality to content characteristics (interactivity and vividness explain the clarity of the content in terms of sensory perception, such as seeing images, hearing sounds or reading stories, and content domain such as education, entertainment, information, and narrative styles, 2) content valence referred to the emotions and feelings associated with the content (anger, anxiety, joy, positive, negative), and 3) content volume related to the frequency and amount of content.

This grouping has also used to study the psychological incentives influenced to the sharing of content by Facebook users (Aladwani, 2017; Fu et al., 2017) who are explained to help create and maintain relationships between customers and organizations, the quality of content on SM i.e. 1) Reflective quality, 2) Stimulated quality, 3) Practiced quality, and 4) Advocated quality. The perception of consumers or recipients' needs would help to create effective content consistent with personal motivation (Fu et al., 2017). Moreover, the previous research also has depicted that the different culture is an obstacle to share knowledge on social media (Din and Haron, 2012). Therefore, content on SM plays an essential role for users from the perspective of both creating information and disseminating information to online communities. From previous research, the study of content on SM has received a lot of interest for business use. On the other hand, there is no clear confirmation of health education.

2.2. Using social media related to health behavior

SM has an undeniable influence on daily life with both positive and negative effects on users, especially with regard to its impact on mental health. For instance, Kraut et al. (1998) has reported that online activities cause users to engage in fewer social interactions leading to problems with psychological well-being. The current study provides a starting point for many further research studies to verify and confirm the results as the variety of activities on SM can be divided into 1) active, including status updates, sharing content or talking, and 2) passive, including viewing pictures, videos or reading content (Deters and Mehl, 2013). The outcomes of the study can be summarized with a simplicity. It is important to understand causes clearly so that the results are both accurate and reliable.

2.2.1. Social media users who have not diagnosed with mental health problems

Over the past few years, the presentation of content on SM has been presented to affect mental health. When users read harmful contents as a result of feeling negative emotions (Aladwani, 2017; Lin and Utz, 2015; Sagioglou and Greitemeyer, 2014), they will compare themselves with others (Jang et al., 2016; Liu et al., 2017), breastfeeding (Wagg et al., 2019), resulting in jealousy linked to depression (Appel et al., 2016; Banjanin et al., 2015). This also affects health and requires intervention in various health behaviors including weight loss (Hales, Davidson and

Table 1. Overview of studies including social media users that have not diagnosed with mental health problems.

Authors, Year	Instrument	Input			Measurements			SM Platform			Activities		Information Factors			Behavioral (Output)					
		Social comparison	Facebook/IG activity	Self-esteem	Neural Network	SEM	Regression	Facebook	Instagram	Txxwitter	Active	Passive	Message factors	Channel factors	Source Factors	Marketing	Intention	Psychological/ Depression	Motivation	Mood	Health
Oeldorf-Hirsch and Sundar (2015)	Control group		●			●		●			●		●				●				
Aladwani (2017)	Self-report		●			●		●	●			●	●						●		
Sagioglou and Greitemeyer (2014)	Self-report		●				●				●		●							●	
Jelenchick et al. (2013)	Self-report		●				●	●			●	●						●			
Lin and Utz (2015)	Self-report	●					●	●				●	●					●			
Hales et al. (2014) (Branley and Covey, 2017)	Instagram post, Facebook groups		●		●		●	●	●	●	●		●								●
Young and Jordan (2013)	Self-report Facebook photos		●			●		●				●	●								●

Turner-McGrievy, 2014) (Dahl, Hales and Turner-McGrievy, 2016), risky sexual behavior (Young and Jordan, 2013), eating (Branley and Covey, 2017), and helping predict other health risk behaviors (Moreno et al., 2011; Zhou et al., 2017). The selection of content on SM is partly influenced by personality (Lin and Utz, 2015), as shown in Table 1.

The results of these studies has demonstrated the role played by content on SM in altering the perceptions and norms of people regarding health behaviors. However, these studies only has focused on general users; they should also pay attention to users with depression while being in a risk group will have an impact on subsequent illness.

2.2.2. Social media users diagnosed with major depressive disorder

The impact of SM on mental health and health behaviors is now discussed more widely in the academic. Several studies focused on education of the health behaviors especially in vulnerable groups with mental health problems try to find the answer and confirm the hypothesis and also bring this study to treat the patients in the clinic (Cairns et al., 2014). For the reason that the depressive disorder was from many causes related to healthy behavior such as eating, exercising, and sleeping habits (Lopresti et al., 2013).

Notably, recent findings on SM activities have shown these play in the role of health behavior interventions in helping support patients with depression, bipolar disorder, schizophrenia, losing weight, and exercise by increasing the intentions to change health behaviors. For example, Naslund et al. (2018) have presented the use of online SM as a strategy to promote health among people with mental health problems.

There have been many studies on SM use in groups with mental health problems, as shown in Table 2, such as patients diagnosed with Major Depressive Disorder, Bipolar Disorder, and Schizophrenia. These have advocated participation in social media to promote health behaviors, including weight loss and exercise (Naslund et al., 2018), and to provide useful information for users (content creation, social connection). However, the study of adverse effects has also received attention, especially with psychological distress leading to the sharing of risky behaviors, cyber bully and self comparison with others (Radovic et al., 2017). However, such studies only have focused on the overall use of SM; they did not focus on any type of activity that directly affects the mind or health risk behavior. Consequently, they did not explain the causal relationship between the effects of SM and behavior. Describing behavioral modifications from the cognitive perspective of the person will elucidate the internal and external factors that influence behavioral changes.

2.3. Health behavior theories (I-Change model)

Health behavior was something happened within a person relating to preventive care and promoting, maintaining, and managing health (Fiske and Taylor, 1991). Variations in the display of healthy behaviors were partly due to the contextual differences of social groups (Conner, 2010). At present, some theories has explained health behaviors by giving stressing the knowledge and understanding of people. There are limitations due to the inability to explain relevant factors with regard to the behavioral change process, as shown in Table 3.

The theory of the above limitations should be improved by the I-Change Model (ICM) (De Vries, Kremers, Smeets, Brug and Eijmael, 2008), consisting of two factors: 1) predisposing factors, demographic and lifestyle information about health (Wulp et al., 2016), 2) information factors i.e. recommendations or information about health related to Message, Channel, and Source (van der Wulp et al., 2015). Thus, modified processes of the health behavior can be linked into 3 phases: 1) pre-motivation explaining the awareness factors in recognizing the advantages or disadvantages and risk perception. 2) motivation describing studies of attitudes, social support and self-efficacy and 3) post-motivation illustrating motivation factors from translating intentions into health behavior changes based on the above factors. It can be helped to understand and fully explain the behavioral changes of a

Table 2. Overview of included studies for social media users diagnosed with major depressive disorder.

Authors, Year	Instrument	Input			Measurements			SM Platform			Activities		Information Factors			Behavioral (Output)					
		Social comparison	Facebook/IG activity	Self-esteem	Descriptive	T-test	ANOVA	Facebook	Instagram	Twitter	Active	Passive	Message factors	Channel factors	Source Factors	Marketing	Intention	Psychological/ Depression	Motivation	Mood	Health
Radovic et al. (2017)	Interview		●		●			●			●							●			
Naslund et al. (2018)	Facebook group lifestyle intervention		●				●	●			●	●	●								●

person's health, as shown in Figure 1. The ICM is a widely popular concept for changing health behaviors, such as predictions of smoking cessation behavior (Rüther et al., 2015), alcohol consumption (van der Wulp et al., 2013; Voogt et al., 2013), sleep behavior (Cassoff et al., 2014), and weight loss (Pajor et al., 2017).

2.4. Perceived risk theory

Recent research has confirmed the perceived ability of individuals to enact behavioral change (de Vries et al., 2005). For example, the concept of perceived risk has received significant attention. Cunningham (1967) has divided risk awareness into six dimensions: 1) performance, 2) financial, 3) opportunity/time, 4) safety/privacy, 5) social, and 6) psychological loss. Perceived risk has used to describe a variety of behaviors: for example of a business perspective, it is used to study how customer purchasing behavior influenced by the perceived quality risk and perceived time risk (Zhang et al., 2012). By exploring a positive influence on risk perception, the acceptance behavior of consumer information has been assessed by the credibility of the source data from e-WOM (electronic word of mouth). At the same time, to perceive the benefits of information, risk perception has also been a positive influence on communication persuasion which leads to the acceptance of consumer information (Hussain et al., 2017).

The perceived risk in relation to performance, financial, time, and privacy is an important factor affecting the intention to use internet banking (Chauhan et al., 2019; Martins et al., 2014), while the factors affected to the intention to use internet corporate banking (CIB) have reduced the importance of performance, financial, time, privacy, security, and social risks (Khedmatgozar and Shahnazi, 2018). Similarly, Park and Tussyadiah (2016) argued that the factors of perceived risk have included 1) performance, i.e., risk of the service not responding, 2) financial risk of additional expenses to get the best service, 3) the risk of losing time or opportunity while using the service, and 4) privacy, i.e., risk of partial disclosure. Moreover, the perceived risk from the use of smartphones would be occurred by increasing the devices. Fong et al. (2017) have reported that the perception of risk is negatively related to the intention to re-use applications such as mobile apps to make hotel reservations. Also, people in the same social context play an important role in creating the same risk perception (Scherer and Cho, 2003).

From a health perspective, the perceived risk in behaviors has led to harm and disease in order to develop the right information to promote. For instance, Duckworth and Lee (2019) have examined the perceptions of risky driving between drivers using alcohol-only or marijuana-only and people using simultaneous alcohol and marijuana (SAM). The SAM users have been increased for the perceived risk of driving safety than single substance users. A survey explored by the relationship between weight status and perceptions of the risk of colorectal (CRC) and breast cancers in women has depicted that non-Hispanic (NH) black women has been at the lowest perception of colorectal cancer risk. Hence, educational programs to support proper nutrition and physical activity planning should be developed by Hall et al. (2019). However, pictorial warnings on cigarette packs have done not directly affected to the perceived risk of smoking cessation (Hall et al., 2018).

Although risk perception will play an important role in supporting and encouraging people to trust and accept information and new technological innovations, if a person perceives a risk to themselves, then this will result in a reduced intention to change behavior. Also, in the health field, the risk of awareness has been to play an important role in creating incentives to prevent health hazards (Ferrer et al., 2018). Key constructs in theories of health behavior have been used to explain and study the perception of health behavior risks (Zanna and Fazio, 1982).

3. Research model and hypotheses

The perspectives on the social media usage of depressed patients and caregivers have affected to change the health behavior of patients in

Table 3. Health behavior theories.

Theory	Authors, Year	Indicator Categories	Outcome Variable
Health Belief Model (HBF)	Rosenstock (1974)	1) Perceived Susceptibility, 2) Perceived Severity, 3) Perceived Threat, 4) Perceived Benefits and Barriers and 5) Cues to Action	Preventive health behavior
Protection Motivation Theory (PMT)	Rogers (1975)	1) Threat Appraisal 1.1 Perceived Severity 1.2 Perceived Susceptibility and 2) Coping Response 2.1 Response Efficacy 2.2 Self-Efficacy	Protection behavior
Theory of Reasoned Action (TRA)	Fishbein (1979)	1) Attitude toward Behavioral and 2) Subjective Norm	Behavioral intention and Behavior
Theory of Planned Behavior (TPB)	Ajzen (1985)	1) Attitude, 2) Subjective norm and 3) Perceived Behavioral Control	Behavioral intention and Behavior
Social-cognitive Theory (SCT)	Bandura (2001)	1) Personal and 2) Environment	Behavior
Information Motivation Behavioral skills theory (IMB)	Fisher et al. (2003)	1) Information and 2) Motivation	Behavioral skills

terms of information and perceived privacy risks required to an understanding of the factors associated with behavioral health interventions. However, there is currently no study in such behavior. Therefore, this study has presented the use of the ICM theory (de Vries et al., 2005) as a framework for explaining modified processes of cognitive behavior to determine the causes of change. For the reason that ICM is suitable for the study of complex behaviors (Ketterer et al., 2014) and can identify factors affecting the behavioral modification process, as shown in Figure 2.

3.1. Predisposing factors

The predisposing factors are divided into three types: 1) sociodemographic (Kinyanda et al., 2011), 2) psychological and clinical, and 3) social factors. They can be used to understand the health behavior, personality, and past treatment history of a sick person (Kinyanda et al., 2011; Stanczyk et al., 2011) to contribute to health behavior modification. For this study, the basic information used is as follows: gender, age, education level, SM platforms used, and the total time spent on these per day (hours).

Every SM platform is different with some unique functions. For example, Facebook is a social networking site that focuses on visualizing social networks, building, and sharing personal information between users in the form of images, videos, or content. Twitter is a microblog being suitable for disseminating information and for sending short messages on real-time user networks. YouTube is classified as a media sharing site, and its distinctive features include a hosting service where users can create videos, photos, and other digital media stored on a server that can distribute data publicly or privately (Grajales et al., 2014). Instagram is a site where not only photos and videos are shared but also hashtags are created to categorize relevant content for sharing between users via tagging (Sabharwal, 2015). In 2019, Instagram usage increased by 4.4% (38 million users) (Kemp, 2019). LINE application is an instant messaging (IM) platform where users can send text, audio, and images in real-time. It also offers Voice over Internet Protocol (VoIP) conversations and video conferences free of charge (Chang and Chang, 2018). The number of users using LINE has increased by 0.6% (Kemp, 2019).

3.2. Information factors

Information factors refer to the level of information received about changing health behaviors including messages, sources, and channels (de Vries et al., 2005; van der Wulp et al., 2013). The content of previous researches published on SM can be described for influencing users' behavior and viewing inappropriate content that may lead to risky behaviors: for example, the content presented to influence disordered eating and risky eating behaviors (offline risk) in women (Branley and Covey, 2017). The proper content of users and the influence of other users also have been essential roles in shaping rebroadcasting behavior (Zhang et al., 2017).

At the same time, recent studies have been confirmed that the information can be influenced to encourage good health behavior. For example, checking the quality of the information in midwives' advice on alcohol usage and pregnancy can be discussed by topics focusing on the source and content of information, while pregnant women and their partners can be commented by advice of a midwife being an essential source of information guiding alcohol used to make decisions during pregnancy (Voogt et al., 2013; Wulp et al., 2016). The information about hereditary cancer (de Vries et al., 2005) has reported that people want to know the type of cancer genetically transmitted to the abnormal symptoms observed through various information channels including the general practitioner, the internet, and leaflets (de Vries et al., 2005). Moreover, Facebook can be helped to promote the health of people with mental health problems through the creation of a secret group to support

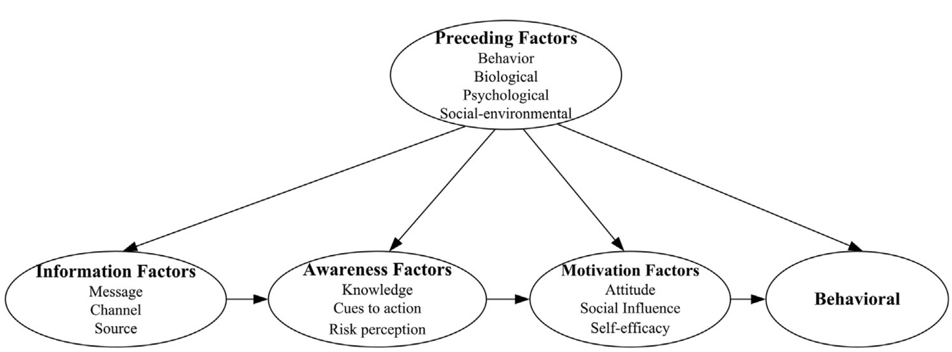

Figure 1. The I-Change Model 2.1. Adapted from the I-Change model in version 2.1 (van der Wulp et al., 2013).[11]

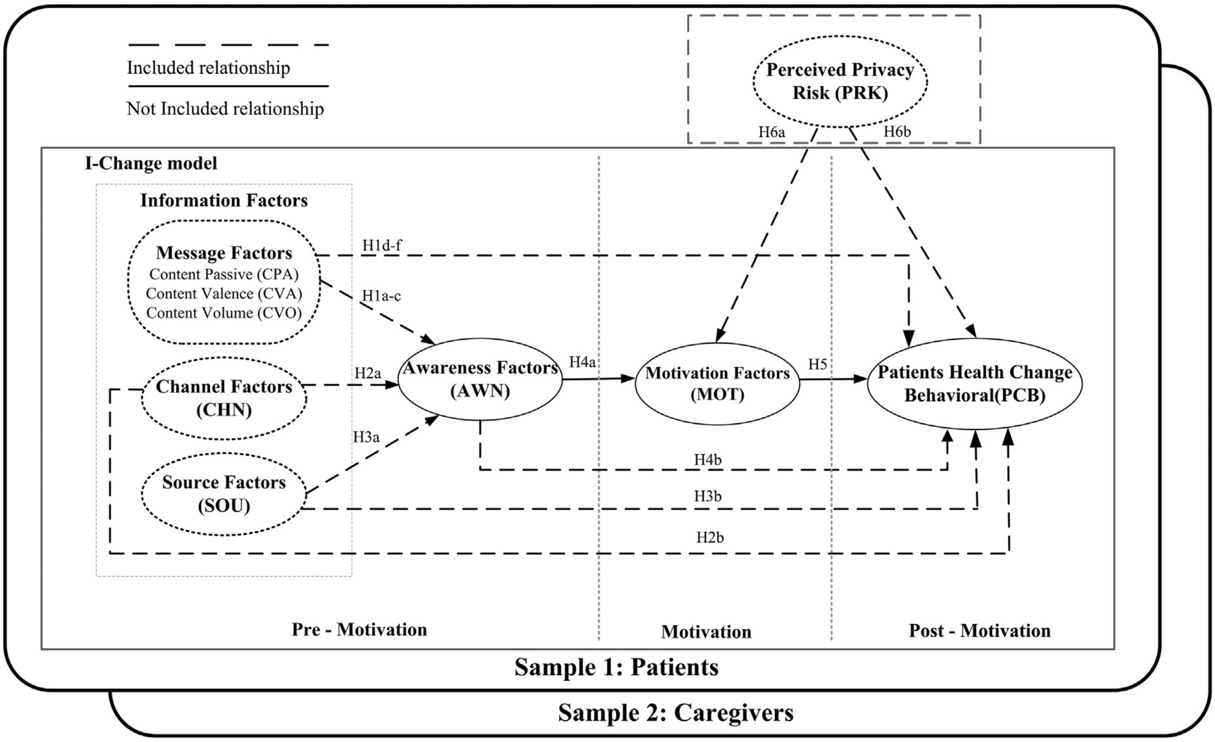

Figure 2. IFPPR proposed research model.

healthy behavioral changes such as weight loss and exercise (Naslund et al., 2018).

This study focuses on three information factors as follows. The Part 1 is the message factors focused on SM content. Peters et al. (2013) have applied sociological and psychological concepts to classify types of online SM content into three categories: 1) content passive (CPA) referred to the clarity of passive content including viewed images, videos, and reading content (Deters and Mehl, 2013), 2) content valence (CVA) related to content telling a story and conveys emotions and feelings, and 3) content volume (CVO) related to the frequency and amount of content received. The Part 2 is channel factors (CHN) described with SM platforms in their different forms such as blogs and microblog groups, content communities, and social networks (Facebook, Instagram, YouTube, and Twitter for example) (Grajales III et al., 2014; Kaplan and Haenlein, 2010). The Part 3 is source factors (SOU) described with sources and recommendations for using SM. The focus in this study is based on the recommendations of experts (Voogt et al., 2013). Therefore, the hypotheses are as follows:

H1a. CPA is positively related to awareness factors in SM use among patients.

H1b. CVA is positively related to awareness factors in SM use among patients.

H1c. CVO is positively related to awareness factors in SM use among patients.

H1d. CPA positively correlates with changing the health behavior of patients by viewing content on SM.

H1e. CVA positively correlates with changing the health behavior of patients by viewing content on SM.

H1f. CVO positively correlates with changing the health behavior of patients by viewing content on SM.

H2a. CHN factor is positively related to awareness factors in SM use among patients.

H2b. CHN factors positively correlates with changing the health behavior of patients by viewing content on SM.

H3a. SOU factor is positively related to awareness factors in SM use among patients.

H3b. SOU factors positively correlates with changing the health behavior of patients by viewing content on SM.

3.3. Awareness factors

Levels of awareness factors indicate that how aware individuals are of good health (van der Wulp et al., 2013). These can be included as follows: 1) their knowledge of behavior capably caused from health hazards (Stanczyk et al., 2011) (Walthouwer et al., 2015), 2) their risk perceptions and awareness of how improper behavior obtained from an adverse effect on health (Wulp et al., 2016) and 3), the cues to action indicated by a change in personal behavior (e.g., price, personal satisfaction). For example, Walthouwer et al. (2015) have confirmed that awareness of one's risk behavior is an essential factor for eating properly. Therefore, it has expected that awareness about correctly the use of SM can affect the motivation to change and any change in patients' health behavior by viewing SM content in a way that is not harmful to health.

This study describes the: 1) knowledge and an assessment of the perceived benefits through the use of SM with affecting heath, 2) risk perceptions and perceived risks from the inappropriate usage of SM, and 3) cues to action (such as internet prices and personal preferences) to the use of SM with people. The following assumptions made:

H4a. AWN factor is positively related to the motivation factor in SM use among patients.

[1] Reprinted from Midwifery, 29(11), Nickie Y. van der Wulp, Ciska Hoving, Hein de Vries, A qualitative investigation of alcohol use advice during pregnancy: Experiences of Dutch midwives, pregnant women and their partners, pp. e89-e98., Copyright (2013), with permission from Elsevier.

H4b. AWN factor positively correlates with the changing health behaviors of patients who view content on SM.

3.4. Motivation factors

Motivation factors (adoption intention) are the levels of motivation or behavior modification related to a person's attitude to behavior modification (Cassoff et al., 2014) (Walthouwer et al., 2015) (Naidoo et al., 2017). For the social influence or social support for behavior modification, individual self-efficacy perceptions of behavioral performance are assessed by perceiving difficult and easy behavior modifications (Rüther et al., 2015) (Wulp et al., 2016) (Pajor et al., 2017). Cassoff et al. (2014) have suggested that positive attitudes are one element of the motivation to change health behavior as a result of evaluating the advantages and disadvantages of behavior modification. This is consistent with a study by Pajor et al. (2017) whose discovery is how the social environment. The positive attitudes to the use of dietary supplements are more likely to influence their use than negative attitudes towards them. In addition, the social influence between partners has an important role in encouraging abstention from alcohol during pregnancy (Wulp et al., 2016). This indicates that the importance of attitude, social influence, and self-efficacy on the motivation would make to change behavior.

This study focuses on the motivation for making changes to health behavior from the perspectives of SM users by evaluating: 1) the positive attitudes of people who perceive both the advantages and disadvantages of using SM, 2) the social influences on people to the use of SM, and 3) the self-efficacy and perceived ability to the use of SM. Therefore, the following assumptions made:

H5. The motivation factor positively correlates with the changing health behaviors of patients who view content on SM.

3.5. Perceived privacy risk

Perceived risk refers to how an individual user acknowledged as the risk of using or predicting their intention to use services and products influenced by various factors (Cunningham, 1967; Bauer, 1960). Previous studies have been reported that security awareness is an important factor in the intention to use mobile applications (Harris et al., 2016). Antheunis, Tates, and Nieboer (2013) describe a major obstacle for patients using SM as a perceived risk to privacy. The study findings has been supported from the idea that risk perception can be motivated with the user to prevent health hazards (Ferrer et al., 2018). This is consistent with the findings of Zanna and Fazio (1982). They have confirmed that risk perception is a key construct being important for explaining health behavior and showing how users' risk perceptions and they are explained and affected by their risk behavior which could lead to danger and disease.

This study is related to health perspectives (health behavior change) and technology (SM). This is focused on the perceived privacy risk to explain SM behavior leading to changes in a patient's health. Therefore, the following assumptions made:

Table 4. Measurement items.

Construct	Item	Survey Item	Source
Content Passive (CPA)	CPA1	Content stuff (video, pictures, music, and links) on social networks is exciting.	Adapted from Salehan et al. (2018) Peters et al. (2013) Deters and Mehl (2013)
	CPA2	Content stuff (video, pictures, music, and links) on social networks has affected my mind.	
	CPA3	Content stuff (Video, pictures, music, and links) on social networks has affected my awareness when using social media.	
Content Valence (CVA)	CVA1	I think the information is told a story and the way of presentation is exciting.	Adapted from Peters et al. (2013) Fu et al. (2017)
	CVA2	I think the information is told a story and the way of presentation is useful to my mind.	
	CVA3	I think the information is told a story and the way of presentation is awareness when using social media.	
Content Volume (CVO)	CVO1	I feel irritated when reading too much shared information from friends on social media.	Adapted from Fu et al. (2017) Choi and Lim (2016) Radovic et al. (2017)
	CVO2	I feel irritated when reading too much shared information from my family on social media.	
	CVO3	I feel irritated when I pay too much attention to social media.	
	CVO4	I have a problem because I use social media too much.	
Channel Factors (CHN)	CHN1	The information that is shown on Facebook, Instagram, YouTube, and Twitter is very interesting.	Adapted from Grajales III et al. (2014) Kaplan and Haenlein (2010)
	CHN2	The information that is shown on Facebook, Instagram, YouTube, and Twitter affects me.	
	CHN3	The information that is shown on Facebook, Instagram, YouTube, and Twitter affects my awareness.	
Source Factors (SOU)	SOU1	Viewing content from my family has an influence on my awareness with regard to using social media.	Adapted from Voogt et al. (2013)
	SOU2	Viewing content from friends has an influence on my awareness with regard to using social media.	
	SOU3	Viewing content that comes from reliable sources influences my awareness with regard to using social media.	
Awareness Factors (AWN)	AWN1	I think using social media is very useful in order to communicate.	Adapted from van der Wulp et al. (2013) Pajor et al. (2017) Stanczyk et al. (2011) Walthouwer et al. (2015)
	AWN2	I perceive the disadvantage of spending too much time on social media.	
	AWN3	The ease of access to social media has influenced me in using social media.	
	AWN4	The cost of accessing social media (internet price) has influenced me in terms of using social media.	
	AWN5	Personal preferences about technology have influenced me in terms of using social media.	
Motivation Factors (MOT)	MOT1	Viewing content on social media is useful for helping me to relax.	Adapted from (Cassoff et al., 2014; Walthouwer et al., 2015) Naidoo et al. (2017) Pajor et al. (2017) Rüther et al. (2015)
	MOT2	Using social media is one way to help me get information about health care.	
	MOT3	Family support is an essential feature for me when using social media.	
	MOT4	Friend support is an essential feature for me when using social media.	
Perceived Privacy Risk (PPR)	PPR1	I pay attention to disclosure of personal information on social media (real name, email, phone number, photo, current town, sexual orientation).	Adapted from Antheunis et al. (2013) Salehan et al. (2018)
	PPR2	I acknowledge that the disclosure of personal information on social media is a risk.	
	PPR3	Privacy risks are an essential part of my decision to use social media.	
Patients Change Behavioral (PCB)	PCB1	Inappropriate social media content may cause changes in my health habits	Adapted from Radovic et al. (2017) Branley and Covey (2017)
	PCB2	Viewing content on social media affects my sleep time.	
	PCB3	Viewing content on social media affects when I eat.	

H6a. Perceived Privacy risk (PPR) is positively related to the motivation factor in decisions made to use SM.

H6b. PPR positively correlates with the changing health behaviors of patients who view content on SM.

3.6. Patients Change Behavioral

Changes in behavior are a measure of how individuals to change their health behavior (van der Wulp et al., 2013). Broekhuizen et al. (2012) have explained that behavioral change in health behavior can be assessed in three main ways: 1) awareness, 2) motivation, and 3) action. When people learn awareness of the risks to their health, they are motivated to change their behavior. This study is focused on explaining the behavior changes related to the topics of eating and sleep disorders after patients have used SM. This is evaluated based on information, awareness, motivation and the perceived privacy risk factors associated with these topics.

4. Research method

4.1. Study participants and setting

To test the hypotheses, a sample was selected from one hospital in Thailand. The research process was conducted from July 2018–February 2019 and approved by The Centre of Ethical Reinforcement for Human Research, Mahidol University, Thailand (MU-CIRB, 2018/058.0503). Research participants were volunteered in response to an invitation from the research assistant (Jang et al., 2016) including explanations of measures to ensure the confidential information (Megan et al., 2013). The participants were agreed to participation in writing. There are samples comprised of 1) 233 patients diagnosed with the major depressive disorder exhibited both mild and moderate symptoms according to the diagnostic criteria of the DSM-5 (Association, 2013), aged 18 years and able to read - write Thai language, and 2) 125 caregivers. The same questions were tested by the both of the patient and caregivers.

The process for the selection of eligible samples is carried out by a psychiatrist and a clinical psychologist. The experts have selected those patients who do not meet the exclusion criteria, as follows: 1) function of severe brain diagnosed by a psychiatrist based on the patient's history during the previous six months, 2) physical diseases posing an obstacle to the assessment, including epilepsy and brain tumors assessed by a psychiatrist and 3) a history of schizophrenia or a schizoaffective disorder assessed by a psychiatrist based on the history of the patient during the previous six months. The criteria of additional withdrawal for individual participants is set so that patients and caregivers can voluntarily withdraw from the program at the discretion of an expert and if patients experience more severe symptoms during the period of the study. The research process has been approved by the research ethics committee at Mahidol University.

4.2. Data collection

The questionnaire was designed according to the framework of the ICM theory to address the health behavior of patients. Questions were divided into two sets, each consisting of 6 parts: Part 1- Characteristics about respondents; Part 2- Information factors; Part 3- Awareness factors; Part 4- Motivation factors; Part 5- Perceived privacy risk factors, and Part 6- Factors underpinning the intention to change behavior. Each question was responded to on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Questionnaire Series 1: Data were collected from patients by clinical psychologists and psychiatric nurses. For prior to data collection, the

Table 5. Baseline demographic characteristics of the participants.

Characteristics	Patients (n = 214) (%)	Caregivers (n = 110) (%)
Gender		
Male	32.7	37.3
Female	67.3	62.7
Age		
Less than 18 olds or less	0.9	0
18–25	25.7	5.5
26–35	55.6	62.7
36–45	15.4	29.1
46–55	2.3	2.7
Education level		
High school or less	12.6	5.5
Some college	40.2	38.2
B.A. or higher	47.2	56.4
Experience of using SM (hours)		
Less than 1 year	8.4	13.6
1–3 years	32.7	29.1
3 years and above	58.9	57.3
SM Platforms used		
Facebook	96.3	93.6
Instagram	22.0	24.0
Twitter	18.0	14.0
Line	93.0	72.0
YouTube	55.0	77.0
Total time per day (hour)		
Less than 1 h	3.7	10.9
1–3 h	51.4	13.6
3–5 h	18.7	60.9
5 h and above	26.2	14.5

Table 6. Measures of internal consistency reliability and convergent validity.

Construct	Composite reliability		Cronbach's α		Average Variance Extracted	
	Self-Report	Family- Report	Self-Report	Family- Report	Self-Report	Family- Report
Content Passive (CPA)	0.921	0.894	0.872	0.823	0.796	0.739
Content Valence (CVA)	0.918	0.893	0.873	0.863	0.79	0.679
Content Volume (CVO)	0.907	0.859	0.864	0.790	0.709	0.604
Channel Factors (CHN)	0.915	0.898	0.861	0.830	0.782	0.745
Source Factors (SOU)	0.915	0.909	0.860	0.853	0.781	0.770
Awareness Factors (AWN)	0.904	0.883	0.889	0.835	0.652	0.601
Motivation Factors (MOT)	0.893	0.891	0.869	0.851	0.675	0.620
Perceived Privacy Risk (PPR)	0.912	0.869	0.859	0.783	0.775	0.689
Patients Change Behavioral (PCB)	0.930	0.886	0.889	0.807	0.816	0.722

Table 7. Loading and cross-loadings of self-report.

Construct	Items	CPA	CVA	CVO	CHN	SOU	AWN	MOT	PPR	PCB
Content Passive (CPA)	CPA1	**0.901**	0.454	0.389	0.436	0.411	0.402	0.260	0.369	0.115
	CPA2	**0.904**	0.453	0.350	0.415	0.405	0.346	0.248	0.378	0.194
	CPA3	**0.871**	0.446	0.366	0.410	0.395	0.351	0.257	0.291	0.243
Content Valence (CVA)	CVA1	0.485	**0.869**	0.353	0.389	0.474	0.388	0.324	0.346	0.201
	CVA2	0.417	**0.871**	0.307	0.348	0.404	0.254	0.236	0.297	0.259
	CVA3	0.398	**0.880**	0.354	0.340	0.339	0.343	0.277	0.356	0.256
Content Volume (CVO)	CVO1	0.449	0.405	**0.814**	0.445	0.367	0.347	0.280	0.279	0.215
	CVO2	0.226	0.285	**0.846**	0.398	0.283	0.440	0.214	0.303	0.094
	CVO3	0.304	0.298	**0.847**	0.417	0.323	0.464	0.281	0.325	0.016
	CVO4	0.424	0.357	**0.861**	0.469	0.299	0.469	0.264	0.274	0.120
Channel Factors (CHN)	CHN1	0.426	0.355	0.468	**0.906**	0.461	0.479	0.190	0.232	0.107
	CHN3	0.427	0.394	0.473	**0.886**	0.504	0.475	0.270	0.305	0.158
	CHN5	0.398	0.333	0.417	**0.861**	0.419	0.391	0.249	0.273	0.267
Source Factors (SOU)	SOU2	0.394	0.376	0.355	0.451	**0.896**	0.443	0.188	0.312	0.202
	SOU3	0.382	0.431	0.292	0.475	**0.899**	0.413	0.178	0.319	0.236
	SOU4	0.419	0.419	0.343	0.458	**0.856**	0.437	0.204	0.310	0.314
Awareness Factors (AWN)	AWN2	0.221	0.249	0.349	0.376	0.414	**0.799**	0.165	0.351	0.047
	AWN4	0.361	0.301	0.387	0.392	0.385	**0.746**	0.100	0.337	0.040
	AWN5	0.335	0.284	0.424	0.364	0.328	**0.777**	0.137	0.427	0.049
	AWN6	0.344	0.304	0.391	0.435	0.380	**0.795**	0.221	0.308	0.034
	AWN8	0.417	0.343	0.497	0.467	0.408	**0.853**	0.267	0.383	0.092
Motivation Factors (MOT)	MOT3	0.181	0.202	0.145	0.170	0.109	0.074	**0.788**	0.242	0.199
	MOT4	0.251	0.220	0.216	0.197	0.093	0.112	**0.776**	0.227	0.195
	MOT5	0.289	0.287	0.348	0.271	0.267	0.307	**0.825**	0.304	0.206
	MOT6	0.258	0.274	0.285	0.263	0.299	0.229	**0.817**	0.246	0.225
Perceived Privacy Risk (PPR)	PPR1	0.284	0.342	0.276	0.265	0.294	0.395	0.220	**0.880**	0.168
	PPR2	0.302	0.240	0.265	0.226	0.263	0.302	0.230	**0.854**	0.128
	PPR3	0.406	0.388	0.361	0.301	0.360	0.425	0.345	**0.906**	0.232
Patients Change Behavioral (PCB)	PCB1	0.173	0.260	0.151	0.190	0.281	0.045	0.271	0.210	**0.919**
	PCB2	0.149	0.225	0.095	0.159	0.189	0.083	0.167	0.214	**0.886**
	PCB3	0.231	0.254	0.093	0.184	0.288	0.023	0.201	0.150	**0.905**

Note: Bold values in represent are loadings for each item that are above the criterion value of 0.7 and an item's loadings on its own variable are higher than all of its cross-loadings with other variable.

patients' readiness to answer the questionnaire were assessed by the use of the Thai Mental State Examination (TMSE) ((Thailand), 1993). Data was collected by talking to patients one at a time in the occupational therapy room of the hospital. When the patient answered a question, the clinical psychologist or psychiatric nurse wrote the answer on the questionnaire to prevent any questions that may stimulate the patient's condition. The patients were also observed and assessed while being interviewed. The data collection will do after the patient has finished the treatment process with the specialist by appointment. The questionnaire was divided into two parts, each lasting 10–20 min.

Questionnaire Series 2: Data was collected from the relatives of patients who had acted as their primary caregivers for at least six months. They did not receive a compensation in the form of hiring for care a patient. The questions in set 2 were the same as those in set 1 used to record patient data but required completion by a caregiver being closely to and able to observe the patient when using SM. The process of collecting caregivers' information has been done while waiting for a specialist to follow-up treatment each time, as shown in Table 4.

Table 8. Loading and cross-loadings of family report.

Construct	Items	CPA	CVA	CVO	CHN	SOU	AWN	MOT	PPR	PCB
Content Passive (CPA)	CPA1	**0.888**	0.213	0.147	0.111	0.124	0.002	-0.021	0.049	-0.112
	CPA2	**0.780**	0.232	0.211	0.122	0.050	0.027	-0.028	0.053	-0.080
	CPA3	**0.906**	0.168	0.179	0.058	0.115	0.062	-0.092	0.113	-0.062
Content Valence (CVA)	CVA1	0.281	**0.740**	0.451	0.268	0.221	0.118	0.043	0.104	-0.047
	CVA2	0.269	**0.784**	0.468	0.418	0.348	0.206	0.095	0.131	0.010
	CVA3	0.129	**0.824**	0.264	0.167	0.092	0.173	0.125	0.133	0.012
	CVA4	0.191	**0.935**	0.413	0.334	0.274	0.448	0.112	0.052	0.156
Content Volume (CVO)	CVO1	0.271	0.476	**0.721**	0.211	0.268	0.121	0.024	0.073	0.087
	CVO2	0.044	0.268	**0.773**	0.126	0.016	0.157	0.116	0.163	0.001
	CVO3	0.131	0.276	**0.834**	0.171	0.123	0.254	-0.068	0.152	0.112
	CVO4	0.220	0.498	**0.778**	0.226	0.240	0.199	0.099	0.107	-0.011
Channel Factors (CHN)	CHN1	0.130	0.380	0.259	**0.854**	0.474	0.352	0.262	0.073	0.104
	CHN3	0.106	0.341	0.228	**0.881**	0.510	0.374	0.156	-0.015	0.141
	CHN5	0.069	0.240	0.130	**0.855**	0.650	0.353	0.068	-0.086	0.290
Source Factors (SOU)	SOU2	0.125	0.218	0.140	0.468	**0.821**	0.196	0.093	0.029	0.057
	SOU3	0.089	0.182	0.124	0.531	**0.900**	0.215	0.079	0.012	0.168
	SOU4	0.097	0.350	0.247	0.655	**0.908**	0.246	0.082	-0.011	0.182
Awareness Factors (AWN)	AWN4	-0.071	0.310	0.242	0.359	0.254	**0.788**	0.246	0.011	0.267
	AWN5	-0.017	0.255	0.203	0.334	0.128	**0.747**	0.022	0.042	0.245
	AWN6	0.011	0.262	0.172	0.359	0.277	**0.750**	0.294	0.112	0.214
	AWN7	0.171	0.327	0.193	0.352	0.200	**0.811**	0.153	0.116	0.247
	AWN8	0.043	0.228	0.141	0.175	0.071	**0.780**	0.150	0.039	0.280
Motivation Factors (MOT)	MOT1	-0.089	0.139	0.035	0.153	0.082	0.154	**0.791**	0.356	0.081
	MOT3	-0.024	0.165	-0.026	0.124	0.112	0.104	**0.758**	0.170	0.174
	MOT4	-0.014	0.115	0.057	0.150	0.038	0.190	**0.714**	0.067	0.069
	MOT5	0.006	-0.008	0.001	0.152	0.109	0.208	**0.839**	0.251	0.023
	MOT6	-0.058	0.082	0.070	0.132	0.030	0.258	**0.829**	0.194	0.096
Perceived Privacy Risk (PPR)	PPR1	0.073	0.067	0.177	-0.029	0.027	0.121	0.225	**0.847**	0.111
	PPR2	0.022	-0.042	0.134	-0.059	-0.056	-0.011	0.153	**0.767**	0.065
	PPR3	0.086	0.170	0.108	0.020	0.024	0.073	0.302	**0.873**	-0.096
Patients Change Behavioral (PCB)	PCB1	-0.056	0.167	0.086	0.197	0.102	0.317	0.206	0.071	**0.872**
	PCB2	-0.156	0.009	0.046	0.139	0.101	0.253	0.012	-0.074	**0.829**
	PCB3	-0.049	0.044	0.042	0.210	0.223	0.247	0.046	0.031	**0.847**

Note: Bold values in represent are loadings for each item that are above the criterion value of 0.7 and an item's loadings on its own variable are higher than all of its cross-loadings with other variable.

4.3. Data analysis

To test the hypotheses, a partial least squares structural equations model (PLS-SEM) with SmartPLS version 3.2.8 was used (Ringle et al., 2015). This is different from covariance-based structural equation modeling (CB-SEM) as it can predict components by amplifying them (Tenenhaus et al., 2005). The reasons for using PLS-SEM were that: 1) PLS-SEM can predict elements to test theories (Zhang and Leidner, 2018), 2) PLS-SEM analyzes the results of measurement models and structural models, 3) PLS-SEM supports data testing in small and medium samples (Chin, 2010), 4) PLS-SEM using SmartPLS software provides an accuracy of both content and classification with regard to composite and reliable

Table 9. Discriminant validity of the measurement model for self-report.

Construct	CPA	CVA	CVO	CHN	SOU	AWN	MOT	PPR	PCB
CPA	**0.808**								
CVA	0.509	**0.884**							
CVO	0.422	0.472	**0.892**						
CHN	0.383	0.406	0.491	**0.889**					
SOU	0.513	0.512	0.411	0.382	**0.842**				
AWN	0.240	0.278	0.302	0.303	0.313	**0.822**			
MOT	0.069	0.194	0.198	0.264	0.126	0.252	**0.903**		
PPR	0.447	0.305	0.388	0.379	0.351	0.313	0.213	**0.880**	
PCB	0.473	0.523	0.452	0.459	0.373	0.246	0.281	0.355	**0.884**

Note: CPA = Content Passive, CVA = Content Valence, CVO = Content Volume, CHA = Channel Factors, SOU = Source Factors, AWN = Awareness Factor, MOT = Motivation Factors, PPR = Perceived Privacy Risk and PCB = Patients Change Behavioral. Bold values in represent are loadings for each item that are above the criterion value of 0.7 and an item's loadings on its own variable are higher than all of its cross-loadings with other variable.

Table 10. Discriminant validity of the measurement model of family-report.

Construct	CPA	CVA	CVO	CHN	SOU	AWN	MOT	PPR	PCB
CPA	**0.860**								
CVA	0.240	**0.824**							
CVO	0.206	0.467	**0.777**						
CHN	0.116	0.365	0.233	**0.863**					
SOU	0.114	0.292	0.200	0.639	**0.877**				
AWN	0.032	0.032	0.032	0.417	0.252	**0.775**			
MOT	-0.051	0.120	0.035	0.180	0.095	0.234	**0.788**		
PPR	0.080	0.103	0.163	-0.017	0.008	0.083	0.288	**0.830**	
PCB	-0.102	0.089	0.069	0.215	0.288	0.083	0.108	0.012	**0.850**

Note: CPA = Content Passive, CVA = Content Valence, CVO = Content Volume, CHA = Channel Factors, SOU = Source Factors, AWN = Awareness Factor, MOT = Motivation Factors, PPR = Perceived Privacy Risk and PCB = Patients Change Behavioral.
Note: Bold values in represent are loadings for each item that are above the criterion value of 0.7 and an item's loadings on its own variable are higher than all of its cross-loadings with other variable.

variance statistics (AVE) (Salehan et al., 2018), and 5) PLS-SEM can effectively solve the problem of non-normal data (Hair et al., 2017). PLS-SEM is therefore the most appropriate method to use the verified results in the form of a measurement model and structural model of patients and caregivers.

5. Results

5.1. Sample characteristics

Initially, there are 233 patients interested in participating this study; however, 19 participants later withdrew because they were no longer interested in participating (n = 8) or were lost to follow-up (n = 11). This left a total of 214 patients and 125 caregivers. However, when examining the questionnaire, only 110 contained complete information (15 incomplete). Table 5 presents demographic characteristics of the sample group. It can be seen that 58.9% of patients had used SM for more than 3 years. The usage percentages of Facebook and Line were approximately 96.3% and 93.0%, respectively. Additionally, 57.3% of caregivers had used SM for more than 3 years. The usage percentages of Facebook and YouTube were approximately 93.6% and 77.0%, respectively.

5.2. Assessment of measurement model

To test the measurement model, Convergent Validity was calculated in accordance with the criteria of Hair et al. (2017) considering composite reliability (CR), Cronbach's α, and Average Variance Extracted (AVE). Table 6 presents the results for internal consistency, reliability, and convergence. It can be seen that the internal consistency of the measurement model was high. For instance, the composite reliability (CR) value was higher than the threshold value of 0.7, the Cronbach's α value was higher than the threshold value of 0.7, and the Average Variance Extracted (AVE) value was higher than the 0.5 thresholds in the first set (patient) and the second set (caregivers).

Discriminant validity was then tested by measuring Cross Loadings to check the reliability of the questions used in the measurement model. It can be considered that the weight of all variables in accordance with a criterion was not less than 0.7. In questionnaire set 1 (patients), the weight value was between 0.746 - 0.919, while in questionnaire set 2 (caregivers), the weight value was between 0.714 - 0.919, as shown in Tables 7 and 8. Discriminant validity also was tested by the use of the criteria of Fornell and Larcker (1981) to measure the relationship between variables in the form of a diagonal matrix where the square roots of AVEs in each construct (bold letters) are greater than in the horizontal

Table 11. Assessment of structural model using bootstrapping.

Hypotheses	Proposed relationship	Patients (n = 218)				Caregivers (n = 110)				Supported
		β	p-value	t-stat	VIF	β	p-value	t-stat	VIF	
H1a	CPA -> AWN	0.085	0.211	1.250	1.569	-0.075	0.489	0.692	1.075	Not Supported
H1b	CVA -> AWN	0.027	0.702	0.382	1.537	0.222	0.037*	2.086	1.440	Caregivers
H1c	CVO -> AWN	0.284	0.000**	4.400	1.475	0.088	0.407	0.829	1.302	Patients
H1d	CPA -> PCB	0.021	0.801	0.252	1.643	-0.118	0.329	0.977	1.095	Not Supported
H1e	CVA -> PCB	0.136	0.098	1.654	1.593	-0.038	0.758	0.308	1.509	Not Supported
H1f	CVO -> PCB	-0.024	0.785	0.273	1.647	0.009	0.941	0.074	1.341	Not Supported
H2a	CHN -> AWN	0.190	0.003**	3.003	1.727	0.348	0.003**	2.982	1.797	Patients, Caregivers
H2b	CHN -> PCB	0.066	0.439	0.774	1.798	0.075	0.567	0.572	2.001	Not Supported
H3a	SOU -> AWN	0.197	0.006**	2.737	1.585	-0.038	0.751	0.318	1.704	Patients
H3b	SOU -> PCB	0.225	0.007**	2.683	1.685	0.066	0.638	0.470	1.709	Patients
H4a	AWN -> MOT	0.109	0.152	1.432	1.230	0.211	0.045*	2.006	1.007	Caregivers
H4b	AWN -> PCB	-0.217	0.012	2.512	1.757	0.315	0.005**	2.841	1.345	Caregivers
H5	MOT -> PCB	0.150	0.049*	1.973	1.210	0.021	0.869	0.165	1.181	Patients
H6a	PPR -> MOT	0.257	0.000**	3.616	1.230	0.271	0.008*	2.652	1.007	Patients, Caregivers
H6b	PPR -> PCB	0.105	0.166	1.387	1.415	-0.005	0.973	0.033	1.142	Not Supported

Note: * = $p < 0.05$, ** = $p < 0.01$, β = Path Coefficients, CPA = Content Passive, CVA = Content Valence, CVO = Content Volume, CHA = Channel Factors, SOU = Source Factors, AWN = Awareness Factor, MOT = Motivation Factors, PPR = Perceived Privacy Risk and PCB = Patients Change Behavioral.

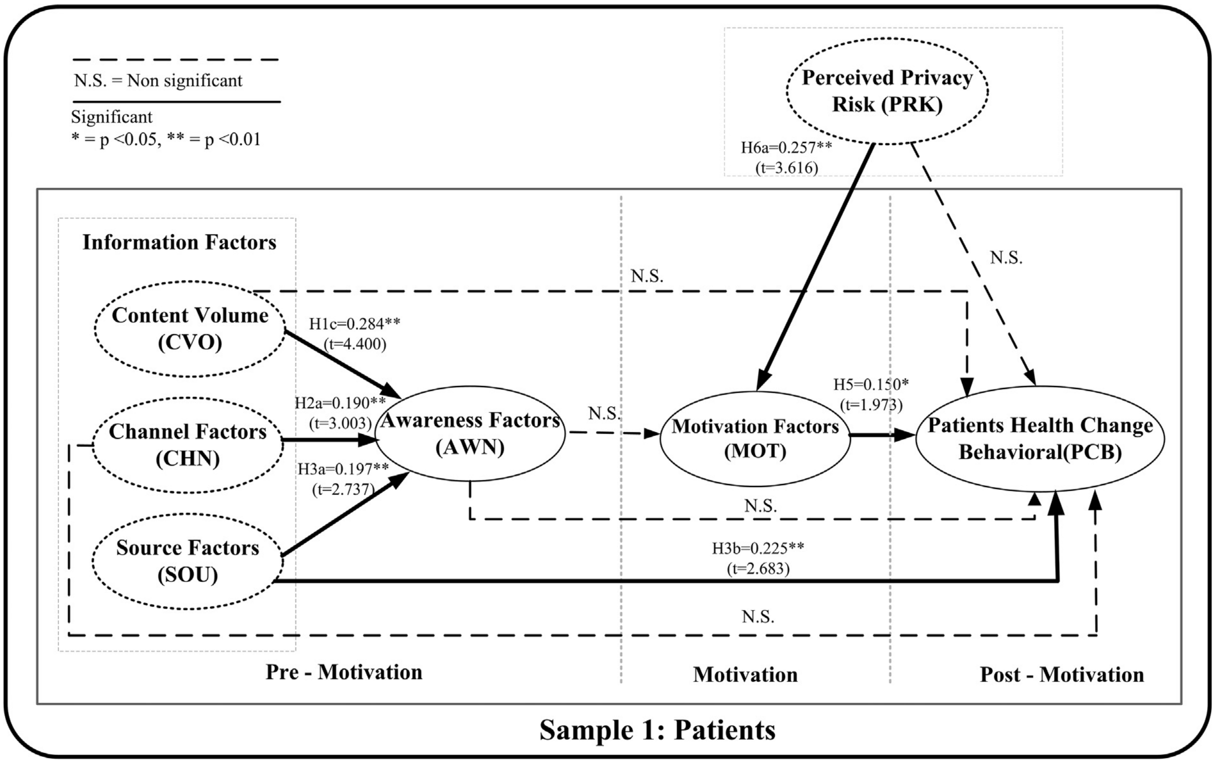

Figure 3. Structural model results of patients.

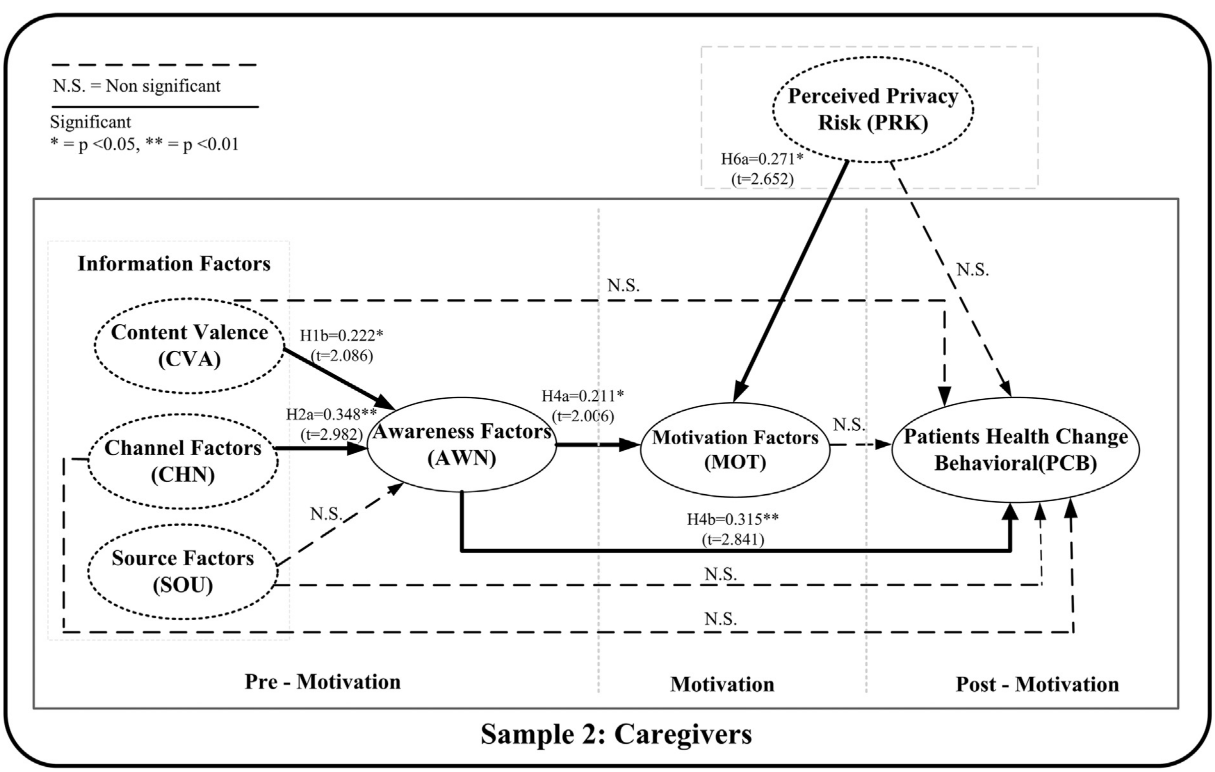

Figure 4. Structural model results of caregivers.

row and corresponding rows. As shown in Tables 9 and 10, discriminant validity was to be at a good level.

5.3. Assessment of structural model

The structural model was tested according to the guidelines of Hair et al. (2017) and Henseler et al. (2016). They has introduced the data resampling with 5,000 bootstrap methods to increase confidence in relationships by considering VIF, Structural Path Coefficients, and Stone-Geisser Q^2 values.

1. VIF inspects the multicollinearity of causal variables having a higher relationship than the acceptable criteria (which must be higher than 3.3). The results showed that the VIF values of both patients and caregivers did not exceed the criteria, and therefore the relationships between the causal variables did not exhibit multicollinearity.
2. Path Coefficients denotes the influences between variables. This study has considered that the path coefficients, p-values, and t-values corresponding to the criteria, namely the t-value were higher than 1.96 (significance level = 5%) and 2.58 (significance level = 1%).
3. Stone-Geisser Q^2 describes the predictive relevance of the model's endogenous constructs using blindfolding techniques. The results of both patient and caregiver data showed that the endogenous latent variables of all 3 values were higher than 0. It can be indicated that the awareness factor, motivation factor, and patients change behavior factor were related to the predictive relevance of the model.

From Table 11, Figure 3 and Figure 4, the results of the analysis of patient data can be revealed that there are six accepted hypotheses. Regarding the data from caregivers, there are five accepted hypotheses. The results of the analysis can be revealed that channel factors are related to a high awareness of the use of social media among patients. At the same time, there is also a strong link between the awareness factors and the changing health behaviors of patients viewing content on social media.

The results of the measurement model and structural models are presented in Tables 6, 7, 8, 9, 10, and 11. It can be seen that the quality of the model is consistent. Discriminant validity is at a reasonable level. All endogenous constructs are associated with the predictive relevance of the model. The consistency of the model with the data has been tested in terms of goodness-of-fit (GoF) according to the criteria of Wetzels et al. (2009). The GoF value in the patient model is to be 0.38 (Large), whilst the GoF value in the caregiver's model is to be 0.32 (Medium). The results of the study have been highlighted as follows: 1) message factors explained for the relationship between a view of contents on social media in the form of content passive, content valence, and content volume; as well as, an influence on awareness factors in the use of social media and behavior modification among patients, 2) new relationships regarding awareness factors and changing behavior as the health of patients is influenced by the contents on social media, and 3) the relationship between perceived privacy risk and motivation factors in the use of online social media among patients and changes of their health behavior affected by viewing social media content.

6. Discussion

This is the first study to utilize the I-Change Model to explain the causal relationship within information factors on social media consisting of 1) message factors (content passive, content valence, and content volume), 2) the channel factor and the source factor, the perceived privacy risk with regard to changing the health behavior of patients influenced by social media content. The research results will explain the perspective of patients and caregivers.

6.1. Patient self-report

The results of the analysis of the I-Change Model constructs from the patient's self-reporting support the six hypotheses as follows. Content Volume has a positive relationship in terms of predicting the awareness factors of using the appropriate social media for the highest number of patients. It can be described that the frequency and the amount of information including advice in terms of using social media will make patients aware of the social media being more beneficial to themselves. This is consistent with previous research related to social media, such as information on how to reduce loneliness (status updating activity) (Deters and Mehl, 2013), to obtain social support, to increase health knowledge, to exchange information and health advice (Antheunis et al., 2013), and to find content related to positive entertainment and humor (Radovic et al., 2017). Clinicians will also be more able to evaluate the mental health and personality of patients through positive online self-presentation (Twomey and O'Reilly, 2017). However, the user might receive information overload until it can make the receiver gotten a confusion, no confidence (Lee and Lee, 2004) and a fatigue (Holton and Chyi, 2012).

Channel factors are positively related to predict the awareness factors concerning the use of appropriate social media on the part of patients. Especially if the patients can access more information using the search channels on websites and Facebook, then they will get a chance to reduce a risk behavior (Park et al., 2019). At the same time, the source factors are also positively related to predict the awareness factors using appropriate social media for patients. This is in accordance with the results of Zhang et al. (2017) that the relationship between data reliability and the influence of other users can be affected to the sharing of user information. It also can be discovered that a new relationship of source factors can directly predict the behavioral changes of the patient health. This is consistent with the research of Wulp et al. (2016) suggested that expert advice is an important source of information for helping patients to be more aware of their health.

A positive relationship within motivation factors in terms of using social media on the part of patients and changing health behaviors of patients is a result of viewing content on social media. Therefore it can be explained that personal motivation using social media has influenced on the intention to change health behaviors and differed according to the content type (Fu et al., 2017). Assessments of the perceived advantages and disadvantages of health behaviors (Cassoff et al., 2014; Walthouwer et al., 2015) in patients especially can be used for health and wellness collaboration with regard to their treatment tended to use social media and to change their health habits more. Therefore, the motivation to use social media can predict the intentions of patients to change health behavior by viewing content on social media.

In addition, the perceived privacy risk is positively related to motivation factors in patients' decision to use social media and has a strong relationship with behavioral change when viewing content on social media. This aligns with Antheunis et al. (2013) who found that the major obstacle to the use of social media in relation to health is the privacy and unreliability of the information. Therefore, if the patient is sensitive to privacy, then the perceived risk of presenting information on social media will motivate them to use safe online social media. Individuals are also influenced by different levels of decision making when using social media (Ross et al., 2009), and the impact of using social media on health means that it is promising educational potential and is now receiving more considerable attention (Banjanin et al., 2015; Hales et al., 2014; Jang et al., 2016; Liu et al., 2017; Nesi et al., 2017; Sagioglou and Greitemeyer, 2014; Zhou et al., 2017). Previous researches have revealed that SM can affect health behavior interventions (Young and Jordan, 2013) and mental health, such as encouraging social comparisons between users (Nisar et al., 2019) (Jang et al., 2016; Liu et al., 2017). Such these results in jealousy are linked to depression (Appel et al., 2016; Banjanin et al., 2015). Posts promoting weight loss (Dahl et al., 2016; Hales et al., 2014) have created an awareness of risk behaviors in relation to gender (Young and Jordan, 2013) as it may lead to eating behavior being harmful in females (Branley and Covey, 2017). The results of this research have shown that the use of social media influences health behaviors due to the perceived privacy risk and motivation factors involved in personal perceptions of social media decisions.

6.2. Family-report

Regarding family-report data from caregivers, Figure 4 shows that content valence transmits personal feelings through stories, enhances relationships, and raises awareness of the use of social media among patients. This aligns with Cheshin et al. (2011) and Coviello et al. (2014) who have explored the influence of communication in the form of emotional messages led to emotional transfer between users. Therefore, it can be recommended that focusing on and monitoring content valence can influence awareness of the use of social media among patients because if patients have read content invoking negative emotions, then it may affect their mind and worsen their illness. The results also have indicated that channel factors can be related to awareness factors in the use of social media among patients at the highest level reflected to the popularity of social media. Currently, there have 2,200 million users especially including facebook (Kemp, 2019) and easily accessed social media channels.

Caregivers can be explained that awareness factors are related to motivation factors in the use of social media among patients and in terms of changing the health behavior of patients when viewing content on social media. Thus, patients who are aware of the benefits of using social media will use it productively. This also linked to changing health behaviors when receiving information and advice on health on social media (Stanczyk et al., 2011; Walthouwer et al., 2015) as a new relationship has emerged between awareness factors related to change the health of patients due to the high level of social media content. If patients can use social media in an inappropriate way, then it may accordingly affect the occurrence of health risk behaviors (Moreno et al., 2011; Zhou et al., 2017). The perceived privacy risk is related to motivation factors in patients' decision to use social media. The results of this analysis are in line with the data from patients' self-report, but there are still some researchers suggested that the risk perceptions sometimes do not predict motivation for disease prevention and still find only generally a few risks when evaluating direct effects (Sheeran et al., 2014).

7. Implication to theories and practices

This study has elaborated on the factors and perceived privacy risks to affect the process for changing the health behavior of patients using SM both theory and practice based on the I-Change framework Model (ICM). The study findings have been presented from the perspectives of patients and caregivers. From a theoretical perspective, the focus is on explaining the causal relationship in three factors as (1) the information factors including the message factors (content passive, content valence, and content volume), (2) channel factors and (3) source factors together with the perceived privacy risk to predict the factors that initiate the process of health behavior change in three phases (awareness, motivation, patients behavioral change). The results of the study for each patient has been described in each phase: Phase 1: Awareness of the appropriate SM used by the patient is directly influenced by content volume, channel factors, and source factors, Phase 2: Motivation of the decision to use SM is directly influenced by the perceived privacy risk, and Phase 3: Patients behavioral change has a direct relationship with source and motivation.

It can be seen that there are 3 phases of caregiver's comments as follows. Phase 1 is content valence directly influenced to awareness of appropriate SM used by patients. For the channel factors and source factors, the patients say that content volume can be predicted for awareness. However, caregivers suggest that content valence is a medium for predicting awareness. This indicates that the caregiver worries about those factors causing an arousal risk in the patient, especially negative content to affect the emotions and to lead the illness. This is why special attention paid to it in this study. Phase 2 is the motivation to make a decision to use SM directly influenced by awareness of and perceived privacy risk. In Phase 3; however, the caregivers say that source and motivation do not have a direct relationship with the patient's behavioral change differed from the patient's perspective. This is also in opposition to the findings of the study by Wulp et al. (2016) who suggest that expert advice is important information for patients' health care decisions. It is possible that the caregiver is concerned about the relationship between the patient and the expert whilst it may lead to a lack of expert advice. It also contradicts the findings of Cassoff et al. (2014) explaining the motivation of a positive attitude by evaluating the advantages and disadvantages of changing the health behavior supported by the willingness to change such behavior. It is possible that caregivers have made proposals to change attitudes and to evaluate the pros and cons of the health care from patients with negative attitudes by assessing the advantages and disadvantages of health care for depressed patients.

This study can be confirmed that there is a relational cause between the factors and perceived privacy risk indirectly influencing the factors relating to the modification process of health behavior such as awareness and motivation. Motivation has a direct relationship to changes in the health behavior of patients. This indicates that both of SM content (content volume and content valence) and channels in the presentation of content can be predicted by changing health behaviors when patients have awareness and motivation in the use of SM. Eventually, motivation and perceived privacy risk can predict behavior change. Although there is recent research into the behavior using SM and the effect on depression, there is no clear link between SM activities and changes in health behavior.

Therefore, the use of passive SM should be monitored to prevent a negative impact on the health behavior of patients and focused on preventing them from reading harmful emotional content and spending too much time on SM. At the same time, experts and caregivers should work together to provide knowledge and advice about the advantages and disadvantages through the use of SM in order to improve awareness and motivation for the proper use of SM among patients. This should include motivating patients to be more aware of the privacy risks due to disclosures of personal information as well as the goal of changing health habits while using SM. These findings should help the experts, patients, and caregivers to understand the relationship between the information and the risks through the use of SM. The information found on SM can be either increased or decreased by patient's symptoms. It also can be led to or prevented in such disease. SM can also be used to provide psychiatric knowledge to those involved in the treatment process leading to more effective results.

7.1. Limitations and future work

This study has analyzed the data from patients using SM from their own and their relative's perspectives based on self-assessment and family reports. The first limitation is the use of surveys and self-assessment reports arisen from the perceptions of patients with depressive disorders that it may already be affected due to the nature of their illness which causes them to have gaps in their knowledge about their previous experience using SM. This may cause disclosure issues leading to inaccurate and incomplete reporting, particularly as the patient's use of SM is an important part of this study. The researchers have tried to account for this limitation by surveying data from family reports. However, the analyzed results from both of the patient's self-assessment reports and the family reports indicate that they are some differences in some relationships. In addition, personal prejudices may also have led to some data analysis relationship errors.

Secondly, this research is a cross-sectional study and provides only short-term explanations for behavioral change. The use of a specific sample means that it lacks demographic and racial diversity. In addition, the depressed patients were not separated into groups in terms of the severity of their illness (mild, moderate, and severe depression). They might have produced different responses and provided information and could have explained their behavior more clearly. Therefore, in the future, the sample groups should be analyzed based on the various levels of depression severity.

In addition, the results of health behavior modification should be explained by viewing contents on social media online as health behavior, in the same way, such as sleeping, eating, taking medicine, or exercising behaviors. It also can be explained for the overall picture of health behaviors only. Therefore, future studies should monitor the long-term effects on patients' symptoms. However, cultural differences should not be ignored to study presentations of passive contents. The cultural differences have been influenced to the sharing of different contents (Din and Haron, 2012). It can lead to the explanation of the adjustment which it can changed to health behaviors from viewing contents on social media in many different perspectives. Finally, this study only focuses on those subjects who joined and educated those patients diagnosed with a major depressive disorder with mild and moderate symptoms in one hospital. It indicates that a lack of diversity in the sample could be means of bias in the findings. The results show that those patients are not well represented with major depressive disorders; as well as, severe and dysthymia symptoms. So, any future research should increase the scope of the study participants and also increase diversity leading to different results.

Although this study will have more limitations, as mentioned earlier, especially in the differences between the views of patients and caregivers, this study also can get the results to identify the relevance of content volume and content valence. Their relevance can be directly a relationship to awareness factors in the use of social media in highest weight from the model. For this reason, the behavioral change model of the risk using social media on a part of patients regarding with the effects of the message, channel, source, and perceived privacy risk; thus, it can be possible to predict and monitor the health behaviors of patients. As the popularity of the use of social media has increased and eased to access online social media, the experts should suggest and monitor an importance of the risk using social media which it also will influence to a higher incidence of disease and a strengthening of symptoms. Therefore, it would go to the prevention of risks associated with the use of social media on a part of patients, and it would provide guidelines for delivering psychiatric knowledge to involve the treatment process.

8. Conclusions

This research has presented an in-depth study of the behavioral modification process through the use of social media on the part of depressed patients. The modeling has been presented under the integration of the I-Change Model framework with the perceived privacy risk of perceived risk theory. Moreover, it can be seen that information factors have been focused on this study whilst the impact of using social media can be proved by analyzing results from the patient's self-report data and confirming the results based on the family-reports of caregivers. The results of this study into the perspective of patients have explained that content volume has a significant role to play in awareness factors of the use of social media among patients. In the opinions of the caregivers, they have suggested that content valence has an important role in awareness factors when the use of social media of patients can be affected to the behavioral changes as a result of viewing content on social media. The same results of the views between the patients and caregivers are channel factors directly affected to awareness factors. Therefore, awareness factors are important keys to be occurred from the use of social media on a part of results from the patients. In addition, the perceived privacy risk has an important role to play in creating motivation factors concerning the decision to use social media on a part of results from the patients.

Declarations

Author contribution statement

A. Leelasantitham, A. Jattamart: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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The authors declare no conflict of interest.

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