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Depression and anxiety in social media: Jordan case study

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A B S T R A C T

The expression "social media" refers to a software-based platform developed for users' benefit. People use it to gain social power, market their products, conduct online business, and share information and ideas. This digital ecosystem has become helpful in various ways, but research indicates that it does not come for free. Addiction, depression, and anxiety are some of the adverse conditions discussed in many studies. The purpose of this study is to mark if there is a relationship between using social media networks and the numbering of people with anxiety or depression. Also, by addressing the need to learn more about what makes people use social networks and how that use affects anxiety and depression in Arabic-speaking users in Jordan, we can help people from different cultures understand each other better. This research uses TAM, telepresence, and survey data from 1050 people, mainly from Jordan. The research looks at how the usage of social media is related to supposed usefulness, supposed ease of use, trust, social influence, age, gender, level of education, marital status, the time spent on the internet, preferred social media network, and perceived usefulness of SNS. AMOS 20 methods of confirmatory factor analysis (CFA), structural equation modeling (SEM), and machine learning (ML), such as SMO, ANN, random forest, and the bagging reduced error pruning tree (RepTree), were used to test the proposed model hypotheses. According to the results, the researchers found high correlations between social network usage and depression and anxiety. The use of social networking sites is also affected by how useful they are seen to be, how easy they are to use, trust, social influence, and telepresence. Also, the moderator's age, gender, level of education, marital status, amount of time spent on the internet, experience with the internet, and favorite social networks all affect how they plan to use social networks.

1. Introduction

Social networking sites (SNS) are technologies that allow users to connect and communicate their views and information. In recent years, many SNSs have developed, like Facebook, Instagram, TikTok, LinkedIn, and WeChat. Some of the SNSs are for entertainment (Facebook), others more for professionals (LinkedIn), text-based, pictorial (Instagram), or movie-based (TikTok). Such SNSs are used, especially in marketing, to connect professionals and exchange ideas. Still, such networks do have a negative effect on users, as seen in many published research papers, i.e., addiction, depression, and anxiety are some of the negative impacts of SNSs (Fox & Moreland, 2015). In this study, the researchers will focus on depression and anxiety

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as two harmful effects of using SNSs in the Arabic culture of Jordan. According to WHO (2017), depression is a mood disorder that causes sadness, loss of attention or desire, guilt, low self-worth, trouble eating or sleeping, exhaustion, and difficulty focusing. On the other hand, anxiety is "*feeling tense, nervous, or unable to relax*" according to the same source. Also, over 300 million people worldwide have depression (4.4%), and 264 million people have anxiety. According to the WHO statistical study in 2017 (WHO, 2017), females' anxiety and depression are more common.

Many studies have examined technology-related stress, loneliness, social isolation, fatigue, depression, anxiety, and addiction. The study proposed by Elhai et al. (2015) investigated how smartphones affect depression and anxiety, also Abu-Taieh et al. (2022a) studied how smartphone addiction can make people feel lonely. Xue et al. (2018) explored smartphone SNS addiction. Sanz-Blas et al. (2019) studied stress, addiction, and fatigue related to Instagram. While Kircaburun and Griffiths (2018) and Frison and Eggermont (2017) looked at how Instagram affects addiction and depression and how Instagram affects loneliness. Dumas et al. (2017) studied narcissism and the longing for likes on SNS Instagram. Keles et al. (2020) investigated the effect of SNS on depression and anxiety. Abu-Taieh et al. (2022b) and Animesh et al. (2011) looked at the link between social networking sites (SNS) and depression and anxiety in a methodical way. Kircaburun and Griffiths (2018) investigated anxiety, depression and social isolation, while Frison & Eggermont, 2017; Pelet et al., 2017) investigated SNS's relation to depression. The following Table 1 presents a synopsis of the studies.

Table 1
Brief of studies that investigated SNS and its influence on Depression and anxiety.

Research	Platform	Negative effect
Elhai et al. (2015)	smartphones	Depression and anxiety
Xue et al. (2018)	smartphone SNS	addiction
Abu-Taieh et al. (2022a), Sanz-Blas et al. (2019)	Instagram	stress, addiction, and fatigue.
Kircaburun & Griffiths (2018)	Instagram	addiction
Frison & Eggermont (2017)	Instagram	depression
Frison & Eggermont (2017)	Instagram	loneliness
Dumas et al. (2017)	Instagram	Narcissism
Fox & Moreland (2015)	Facebook	stress
Keles et al. (2020)	SNS	depression, anxiety
Abu-Taieh et al. (2022b), Kircaburun & Griffiths (2018)	SNS	depression, anxiety, and social isolation.
Frison & Eggermont, (2017)	SNS	depression
Pelet et al., (2017)	SNS	depression
Animesh et al. (2011)	SNS	Depression and Anxiety

To date, attention has been focused on depression or anxiety in using SNSs. Nonetheless, in Arabic culture, a thorough analysis of SNS use and the association between depression and anxiety is lacking (WHO, 2017; Ongsakul et al., 2014; Merrill et al., 2022; Li et al., 2022; Baabdullah, 2018; Lu & Yang, 2014; Suki & Ramayah, 2012). So, this study aims to investigate and figure out what cause's depression and anxiety in adults in Jordan when they use social networks. Accordingly, the following study questions were addressed by this study:

Question 1: What are the influences that affect SNS usage, which influences depression and anxiety?
Question 2: Is there a relationship between depression and anxiety and social networks use?

In particular, the current research examines how perceived ease of use (PEoU), perceived usefulness (PU), social influence (SI), trust (TR), and telepresence (TEL) affect SNS use. It also wants to look at how SNS use affects anxiety and depression. This study looks at how age, gender, level of education, marital status, time spent online, preferred SNS, and internet practice affects how people use SNS. The motivation for this research is that mental well-being is as important as physical well-being. This research shows that there isn't much research on depression and anxiety in the Arabic-speaking world related to social media networking sites (SNS). As a result, the telepresence of a person when using SNS is a crucial part of this research. This research is essential because of how depression and anxiety affect how people plan to use social networking sites. In different studies, the researchers mentioned the rewards and problems of using SNSs. This research will investigate the affecting factors of behavioral intention toward SNS usage and its impact on anxiety and depression among Arabic-speaking Jordanians.

The main contribution of this study is that it investigates and tests the proposed model, which has five independent determinants, one intermediate determinant, seven moderating determinants, and two dependent determinants. Accordingly, the study intended to determine the factors influencing SNS users' anxiety and depression among Jordanian adults. So far as the researcher knows, there hasn't been a single study of SNS use and its relationship with depression and anxiety that considers all these factors.

The observed results offer a number of key findings. Depression and anxiety are influenced by SNS usage. Social influence (SI), trust (TR), Perceived ease of use (PEoU), perceived usefulness (PU), and telepresence (TEL) all play a role in how people use SNS. Also, how people use SNS depends on their age, gender, level of education, marital status, time spent online, which SNS they prefer, and how much experience they have with the internet. This study is structured as follows: section 2 presents the theoretical framework of the proposed model and the hypotheses. Subsequently, the research methods are shown, which include research demographics and data analysis and validation in addition to the ML prediction. The outcomes of the data analysis are debated in the next section. Along with the theoretical and practical suggestions, the study's limitations are reviewed, and suggestions are made for future research.

2. Theoretical Framework and Hypotheses Development

The purported model is presented in Fig. 1, motivated by TAM suggested by Davis (1989), in addition to trust and social influence constructs assumed from the TAM extended model (Siau & Shen, 2003; Gefen et al., 2003), accompanied by seven moderating factors. This article cites more than 15 research articles on the impact of social media (Sanz-Blas et al., 2019; Pelet et al., 2017; Suki & Ramayah, 2012). The model's constructs include five independent variables: PU, PEoU, TR, SI and TEL variables. The model indicates that the five independent factors affect the behavioral intention to use social media networks (Lu & Yang, 2014; Suki & Ramayah, 2012). Also, depression and anxiety are two dependent variables affected by behavioral intention (Meshi & Ellithorpe, 2021; Merrill et al., 2022; Li et al., 2022). Also, the seven moderating variables are age, gender, marital status, favorite social network, time spent on social media, internet experience, and level of education (Samsudeen et al., 2022; Smeda et al., 2017). Accordingly, 14 hypotheses were postulated based on the proposed model. The suggested model and hypotheses development will be considered in detail in the following sections. Davis (1989) developed the Technology Acceptance Model (TAM), the most crucial research model used to describe, figure out, and explain how people adopt the latest technological innovations. Factors like ease of use, usefulness, and behavioral intention are used when people use and adopt new technologies. Ease of use and usefulness are the essential TAM variables for predicting how people will use and accept new technologies. Davis (1989) say that the perceived usefulness and ease of use directly affect the intention to use. The level of interest in using the system is defined as an attitude that leads to plans for behavior and the actual adoption and use of the system. Many important factors determine whether someone will use or adopt a new technology based on how they plan to act when they use or embrace it. Two main factors affect behavior intention to adopt and use new technology: perceived usefulness and perceived ease of use (Davis, 1989; Dixit & Prakash, 2018). Conferring to Davis (1989), perceived usefulness is defined as the "*subjective perception of users where they believe that using certain technologies can improve the performance of their work"*. According to previous research, people are more expected to accept and use social media if they believe it will increase their value and productivity (Pelet et al., 2017; Suki & Ramayah, 2012; Dixit & Prakash, 2018). Kwon & Wen (2010), Pelet et al., 2017, and Dixit & Prakash (2018) all investigated the link between how useful people thought social networks were and their plans to join and use them. Dixit & Prakash (2018) found that people's plans to use social networks are not affected by how useful they think they are. On the other side, Suki & Ramayah (2012) and Hansen et al. (2018) found that a person's willingness to use social networks is significantly influenced by how useful they think social networks are. Accordingly, hypotheses H1 and H2 are proposed:

H1: *Perceived usefulness (PU) positively influences the individual's behavioral intention (BI) to use social media.*

Davis (1989), perceived ease of use was defined as "the degree to which a person believes that using a particular system would be free of effort". Dixit & Prakash (2018), Suki & Ramayah (2012), and Hansen et al. (2018) investigated how perceived ease of use influences people's intentions to use social networks. They found that how easy people think it is to use significantly impacts how likely they are to join and use social networks.

H2: *Perceived ease of use (PEoU) positively influences the individual's behavioral intention (BI) to use social media*.

According to Siau & Shen, (2003) trust is considered one of the critical factors that should be an integral part of TAM model. Morgan & Hunt (1994), Tiwari et al. (2021), De Wulf et al. (2001) indicated that trust is the individuals' positive perception of consistency, reliability, and integrity. Tiwari et al. (2021) said that most people don't use financial apps or services on their phones because they don't trust them. Khan et al. (2021) investigated what makes people ready to use social media to access e-government services. In their study, Hansen et al. (2018) found that trust in social networks plays a crucial role in consumer decision-making regarding consumers' use of social networks for transactions. Also, studies (Baabdullah, 2018; Hansen et al., 2018; Tiwari et al., 2021; Alalwan et al., 2017; Alalwan et al., 2018) have shown that trust significantly affects people's plans to accept and use new technologies. Thus, the following hypothesis is proposed:

H3: *Trust (TR) positively influences the individual's behavioral intention (BI) to use social media.*

Venkatesh et al. (2003) described social influence as "the extent to which an individual perceives that important others believe he or she should apply the new system". Camilleri (2020) and Venkatesh et al. (2012) say that social influence is related to a person's choice to accept, adopt, and use new technology, which may be influenced and motivated by essential people, close family members, friends, and others in the community. Researchers have already found that social influence significantly affects a person's decision to join and use social networks (Pentina et al., 2012; Usman & Okafor, 2019). So, this study uses social influence to determine how much people influence others to join and use social networks. Hereafter, the subsequent hypothesis is postulated:

H4: *Social influence (SI) positively influences the behavioral intention (BI) to use social media.*

Telepresence is the individuals' perceived sense of being engaged in a simulated environment replicated by a digital application or a game, which gives the individuals the sensation that they are a part of the action (Nah et al., 2011; Faiola et al., 2013). Animesh et al. (2011) and Saunders et al. (2011) reported that telepresence positively affects people's behavioral responses, flow, and perceived enjoyment. Yang and Gong (2021) state that video gamers usually become wholly immersed in the flow of a game, which makes them lose track of time and feel great. Lee (2018) and Ongsakul et al. (2014) found that telepresence makes people more likely to act in a certain way on hotel websites. Kwak et al. (2014) reported that telepresence positively affects social network service use. Also, Pelet et al. (2017) investigated how the overall flow experience, telepresence, and how often people use social media are related. They found that the overall flow experience is crucial to how telepresence makes people more likely to use social media. Lee et al. (2020) also found that telepresence makes people more likely to visit websites that are based on virtual reality (VR). Therefore, the following hypothesis:

H5: *Telepresence (TEL) positively influences an individual's behavioral intention (BI) to use social media.*

According to Venkatesh et al. (2003), behavioral intention is "*the dependent factor which assesses the behaviors of the individuals towards the used technological service*." People's behavioral intentions are their desire and willingness to do activities and actions that will lead to profitable results as planned and expected (Abu-Taieh et al., 2022c, AlHadid et al., 2022) . When people's actions are affected by their behavioral intentions, they make an excellent effort to partake in activities that will give them the benefits and services they want (Alalwan et al., 2015, Baabdullah, 2018; Alalwan et al., 2018; Dwivedi et al., 2019, Masa'deh et al., 2022). Previous studies (McCord et al., 2014; Meshi & Ellithorpe, 2021; Merrill et al., 2022; Marino et al., 2018; Huang, 2022) investigated the association between behavioral intention and social media use and psychological distress, including depression and anxiety. Dobson (1985) defined anxiety as "an affective, physiological, cognitive, and behavioral state" and added that "anxiety is considered to be one of unfocused arousal, discomforting to the person involved, and a state to *be avoided*." On the other hand, Dobson (1985) defined depression "as a multifaceted state that eventuates from a perception of an important loss or threat of such a loss." Seabrook et al. (2016) argue that depression is associated with individuals' negative social network interactions. Merrill et al. (2022) and Li et al. (2022) found that using social media more led to depression in a significant and linear way. McCord et al. (2014) reported that Facebook users would be positively related to social anxiety. Also, McCord et al. (2014) stated that individuals with high anxiety use Facebook to pass the time and to feel less lonely than those with low anxiety. Also, Marino et al. (2018) found that more time spent on Facebook is linked to more anxiety and depression. Also, Huang (2022) proved that using social networks more is linked to having more anxiety and depression. In this study, the anxiety items were measured using four items, while the depression items were measured using six items. The Patient-Reported Outcomes Measurement Information System (PROMIS) (Pilkonis et al., 2011) was used to get all the items about anxiety and depression. As a result, the subsequent hypotheses are anticipated:

H6: *Behavioral intention (BI) to use social media positively affects individuals' depression.*
H7: *Behavioral intention (BI) to use social media positively affects individuals' anxiety*.

Researchers have looked at people's plans to use social media based on their age, gender, level of education, amount of time spent on the internet, and other factors (Davis, 1989; Kwateng et al., 2018; Samsudeen et al., 2022; Venkatesh et al., 2012). Researchers looked at how people's age and their plans to use social media related to each other. researchers (Pfeil et al., 2009; Lu & Yang, 2014; Suki & Ramayah, 2012; Zaphiris et al., 2007) found that older individuals usually have different expectations and attitudes about new technologies, which makes it harder for them to recognize the potential benefits. At the same time, younger generations are more open and accepting of new technology. Also, Blank & Lutz (2017) found that a person's age significantly affects how likely they are to use Facebook and Twitter. On the other hand, Leong et al. (2013) found that people's age did not change how they used and adopted mobile entertainment. Consequently, the next hypothesis is suggested:

H8: *Age positively influences the behavioral intention (BI) to use social media.*

Meanwhile, previous studies inspected the association between gender and behavioral intention (BI) to use social media. Faiola et al. (2013) said that the gender of a person did not affect their behavioral intention (BI) to use social media. Also, Leong et al. (2013) and Blank & Lutz (2017) confirmed that Facebook adoption and use are influenced by gender, while LinkedIn and Twitter adoption is not affected by individuals' gender. Consequently, the following hypothesis is suggested:

H9: *Gender positively affects the behavioral intention (BI) to use social media*.

Leong et al. (2013) and Blank & Lutz (2017) looked at the association between education level, the intention to use social media, and marital status. Leong et al. (2013) reported that education level and marital status did not affect the use and adoption of mobile entertainment.
The mentioned factors need further investigation. Also, Blank & Lutz (2017) found that an individual's educational level does not influence the use of Facebook, Instagram, LinkedIn, and Twitter. On the other hand, Blank & Lutz (2017) reported that separated individuals are pointedly more expected to adopt and use LinkedIn than single people. Therefore, the following hypotheses are anticipated:

H10: *Education level positively affects behavioral intention (BI) to use social media.*
H11: *Parental Marital status positively affects behavioral intention (BI) to use social media.*

In accordance with O'Connor et al. (2013), the amount of time consumed on social media is the "*frequency and duration that youth are engaged in screen media use*." Tourinho & de Oliveira (2019) claimed that people are increasingly using social media technologies, both in terms of how many people use them and how much time they spend on social media networking sites. Sanz-Blas et al. (2019) stated that social media overuse and an absence of control over time consumed using networking applications are the leading reasons of social media use and addiction. Hence, the following hypothesis:

H12: *Time spent using social media positively influences the behavioral intention (BI) to use social media.*

According to Statista (2022), the most widespread SNS is Facebook, followed by YouTube, WhatsApp, Instagram, WeChat, and TikTok. Chuang et al. (2017) and McCord et al. (2014) studied the social and behavioral intentions of using Facebook for social networking. Sanz-Blas et al. (2019) studied the effect of Instagram overuse on "emotional fatigue" and addiction. Also, Blank & Lutz (2017) looked at how social media networks are represented in the UK and how people plan to use Facebook, LinkedIn, Twitter, Pinterest, and Instagram. Consequently, we propose the following hypothesis:

H13: *Favorite Social Media Network positively affects behavioral intention (BI) to use social media.*

Internet experience is regarded as a significant factor affecting the adoption of new technologies (Davis, 1989; Venkatesh et al., 2003; and Chawla & Joshi (2020). According to Davis (1989), "*consumers are more likely to experience the hassles of learning difficult-to-handle functions, and yet they are considered important to them.*" Venkatesh et al. (2012) studied the effects of age, gender, and experience on the UTAUT model. Campisi et al. (2015) found that the frequency of internet use improves the individual's knowledge and experiences. Morris & Venkatesh (2000) and Trocchia & Janda (2000) found that youth usually are more experienced with the internet, while older people have trouble and problems when using the internet. Hereafter, the following hypothesis was suggested:

H14: *Internet experience positively affects behavioral intention (BI) to use social media.*

The following sections discuss the research methods, data analysis, and results.

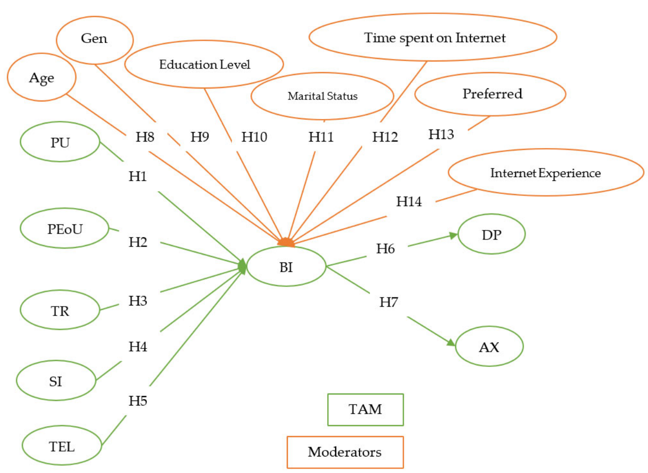

Fig. 1. Proposed model

3. Research Methods

The research study intended to study the effect of SNS user behavior on the anxiety and depression of adults in Jordan. The first part of the research study looked at the effects of the independent variables PU, PEoU, TR, SI, and Tel on the mediating variable BI. There wasn't much more research on how behavioral intention (BI) affects depression and anxiety in adults in Jordan. After a long time developing the research, the investigators advanced the research model revealed in Figure 1 and the research hypotheses. Also, a survey questionnaire was made and evaluated, and then 1050 participants were chosen at random to give their information.

3.1. Research Context

SNS is becoming a part of our lives, and people use SNS for various reasons. LinkedIn is an SNS for professionals, while Facebook is used socially to communicate with friends and family members or to communicate with others. Kids use different

SNSs like YouTube for Kids, Instagram, or TikTok. The other side of SNSs that carry negative connotations like addiction, depression, and anxiety.

3.2. The Measures

So as to examine the proposed research model suggested for this study, a questionnaire survey was designed on the basis preceding studies. There are 2 dependent constructs, 5 direct variables, and 1 intermediate variable. There are also 7 moderating variables. The variable of Perceived usefulness (PU) was measured by 4 items approved from Bashir & Madhavaiah (2015). Also, Perceived ease of use (PEoU) was measured by 4 items adopted from Bashir & Madhavaiah (2015). The variable of Trust (TR) was evaluated by 5 items approved from Baabdullah et al. (2019). Also, Social Influence (SI) was measured by 4 items adopted from Puriwat and Tripopsakul (2021). Telepresence (TEL) was assessed by 4 items approved from (Animesh et al., 2011; Saunders et al., 2011; Pelet et al., 2017). Also, Behavioral intention (BI) was determined by 4 items adopted from Puriwat & Tripopsakul (2021). Anxiety (AX) was measured by 4 items approved from (Pilkonis et al., 2011), while depression (DP) was measured by 6 items adopted from (Pilkonis et al., 2011).

3.3. Participants and Procedure

A 5-point Likert scale was performed, starting from "strongly disagree" (1) to "strongly agree" (5), an Arabic and English Google Docs survey questionnaire were made. Also, a board of five academics revised the survey. Comments were composed, and the survey was remedied consequently. So, the study was tested on 25 SNS users in Jordan to ensure that the questions were understandable. Revisions were made to the survey. From May 24 to June 24, 2022, the survey was conducted on 1050 SNS users in Jordan via email, Facebook Messenger, WhatsApp, Telegram, and Facebook groups. Table 2 reveals the demographic outline of the respondents for the current study that they were nearly alike in terms of relatives (i.e., males and females), married, held diplomas and bachelor's degrees, had good or excellent internet experience, and spent five hours or more on social media, specifically Snapchat and Instagram.

Table 2
Demographic profiles of the respondents.

Group	Group	Frequency	Percentage%
Gender	Male	533	50.8
	Female	517	49.2
	Total	**1050**	**100.0**
Age (Year)	18 - less than 28	101	9.6
	28 - less than 38	747	71.1
	38 - less than 48	189	18.0
	48 - less than 58	13	1.2
	58 and over	0	0.0
	Total	**1050**	**100.0**
Educational level	High school and less	7	0.7
	Diploma	437	41.6
	Bachelor	430	41.0
	Master	160	15.2
	PhD	16	1.5
	Total	**1050**	**100.0**
Marital Status	Single	243	23.1
	Married	519	49.4
	Divorced	288	27.4
	Total	**1050**	**100.0**
Internet Experience	Low	15	1.4
	Good	804	76.6
	Excellent	231	22.0
	Total	**1050**	**100.0**
Time Spent on social media (Hours)	One	15	1.4
	Two	40	3.8
	Three	481	45.8
	Four	34	3.2
	Five and more	480	45.7
	Total	**1050**	**100.0**
Favorite Social Network Used Most of the Time	Facebook	78	7.4
	Twitter	3	0.3
	Titoki	17	1.6
	Snapchat	445	42.4
	LinkedIn	1	0.1
	YouTube	23	2.2
	Instagram	325	31.0
	Other	158	15.0
	Total	**1050**	**100.0**

4. Analyses and Findings

4.1. Descriptive Statistical Analysis

According to Pallant (2020), Sekaran & Bougie (2016), the mean and standard deviation were calculated to define the answers and therefore the attitude of the respondents to each individual question enquired in the survey. The level of each item was determined by the next method: (highest point on the Likert scale – the lowest point on the Likert scale)/the number of the levels used = (5-1)/5 = 0.80, where 1-1.80 was echoed by "very low", 1.81-2.60 reflected by "low", 2.61-3.40 reflected by "moderate", 3.41-4.20 echoed by "high", and 4.21-5 reflected by "very high" . Tables 3 and 4 summarize the outcomes.

Table 3
The overall mean and sd. of the research variables

Type of variable	Variables	Mean	Standard Deviation (SD)	Level	Order
Independent variables	Perceived Usefulness (PU)	4.3910	0.31322	Very High	4
	Perceived Ease of Use (PEoU)	4.4502	0.25547	Very High	3
	Trust (TR)	2.7141	1.16765	Moderate	5
	Social Influence (SI)	4.4810	0.60547	Very High	1
	Telepresence (TEL)	4.4810	0.73154	Very High	2
Mediating Variable	Behavioral Intention (BI)	4.6260	0.63306	Very High	-
Dependent Variable	Depression (DP)	4.2468	0.84383	Very High	2
	Anxiety (AX)	4.4643	0.82885	Very High	1

As shown in the previous table, Table 3, the outcomes of the data analysis demonstrate that all the research variables are used at very high levels. In contrast, respondents' trust attributes occur moderately, with a mean of 2.7141. However, the next table, Table 4 displays the scores for each variable's items.

Table 4
Mean, and standard deviation, Level, and order of the study's variables

Perceived Usefulness (PU)	**Mean**	**SD**	**Level**	**Order**
PU1	4.11	0.723	High	5
PU2	4.71	0.524	Very High	2
PU3	4.15	0.485	High	3
PU4	4.86	0.431	Very High	1
PU5	4.13	0.527	High	4
Perceived Ease of Use (PEoU)	Mean	SD	Level	Order
PEoU 1	4.19	0.437	High	3
PEoU 2	4.70	0.516	Very High	2
PEoU 3	4.73	0.477	Very High	1
PEoU 4	4.18	0.458	High	4
Trust (TR)	Mean	SD	Level	Order
TR1	2.70	0.955	Moderate	3
TR2	2.96	1.347	Moderate	1
TR3	2.53	1.120	Moderate	5
TR4	2.82	1.489	Moderate	2
TR5	2.56	1.119	Moderate	4
Social Influence (SI)	Mean	SD	Level	Order
SI1	4.77	0.615	Very High	2
SI2	4.73	0.699	Very High	3
SI3	4.32	0.696	Very High	4
SI4	4.76	0.644	Very High	1
Telepresence (TEL)	Mean	SD	Level	Order
TEL1	4.71	0.764	Very High	1
TEL2	4.25	0.855	Very High	4
TEL3	4.29	0.782	Very High	3
TEL4	4.68	0.843	Very High	2
Behavioral Intention (BI)	Mean	SD	Level	Order
BI1	4.28	0.777	Very High	4
BI2	4.76	0.648	Very High	2
BI3	4.78	0.616	Very High	1
BI4	4.69	0.808	Very High	3
Depression (DP)	Mean	SD	Level	Order
DP1	4.03	0.906	High	4
DP2	3.77	0.695	High	6
DP3	4.58	1.003	Very High	3
DP4	4.60	0.982	Very High	1
DP5	4.59	0.996	Very High	2
DP6	3.91	0.820	High	5
Anxiety (AX)	Mean	SD	Level	Order
AX1	4.25	0.837	Very High	4
AX2	4.63	0.918	Very High	1
AX3	4.36	0.910	Very High	3
AX4	4.61	0.960	Very High	2

Table 5
The ultimate measurement model properties.

Constructs and Indicators	Factor Loadings	Std. Error	Square Multiple Correlation	Error Variance (ER)	Cronbach Alpha	Composite Reliability (CR)*	AVE**
Perceived Usefulness (PU)					0.757	0.88	0.92
PU1	0.901	***	0.921	0.111			
PU2	0.582	0.020	0.339	0.181			
Perceived Ease of Use (PEoU)					0.910	0.87	0.90
PEoU1	0.926	***	0.858	0.270			
PEoU2	0.437	0.038	0.191	0.216			
PEoU3	0.471	0.035	0.221	0.177			
PEoU4	0.891	0.029	0.794	0.430			
Trust (TR)					0.977	0.95	0.96
TR1	0.924	***	0.854	0.133			
TR2	0.932	0.025	0.868	0.239			
TR3	0.975	0.018	0.952	0.160			
TR4	0.979	0.024	0.958	0.290			
TR5	0.975	0.018	0.951	0.260			
Social Influence (SI)					0.932	0.88	0.90
SI1	0.938	***	0.879	0.460			
SI2	0.959	0.018	0.920	0.390			
SI3	0.712	0.028	0.506	0.239			
SI4	0.930	0.018	0.865	0.560			
Telepresence (TEL)					0.923	0.95	0.81
TEL1	0.903	***	0.815	0.108			
TEL2	0.857	0.026	0.735	0.193			
TEL3	0.786	0.026	0.618	0.234			
TEL4	0.895	0.024	0.802	0.141			
Behavioral Intention (BI)					0.906	0.84	0.87
BI1	0.677	***	0.459	0.327			
BI2	0.907	0.042	0.823	0.470			
BI3	0.909	0.040	0.826	0.660			
BI4	0.938	0.052	0.880	0.790			
Depression (DP)					0.969	0.93	0.68
DP1	0.837	***	0.701	0.246			
DP2	0.919	0.020	0.844	0.570			
DP3	0.975	0.028	0.951	0.490			
DP4	0.969	0.027	0.939	0.590			
DP5	0.984	0.027	0.969	0.310			
DP6	0.841	0.026	0.708	0.196			
Anxiety (AX)					0.934	0.91	0.71
AX1	0.771	***	0.595	0.283			
AX2	0.970	0.037	0.942	0.490			
AX3	0.846	0.039	0.716	0.235			
AX4	0.985	0.039	0.969	0.280			

* Employing Fornell & Larcker (1981) formula
** The formula for the variance extracted
*** Zero Value

4.2. "Structural Equation Modeling Analysis"

"Structural equation modeling analysis" was used in this section to examine the study's hypotheses. The properties of the tool items were examined using a first confirmation factor analysis (CFA). The study's propositions were evaluated using SEM with Amos 20. The third section presented the moderating construct effects. Using five machine learning techniques, the results were then validated and verified.

4.2.1. Measurement Model

A" CFA" test was conducted to determine the properties of the items of the instrument. The measurement model specifies how latent variables or hypothetical constructs are calculated in terms of observed variables and embodies the validity and reliability of observed variable responses to latent variables (Bagozzi & Yi, 1988; Black & Babin, 2019; Newkirk & Lederer, 2006; Kline, 2015). Table (4) presents the variables' factor loadings, Cronbach alpha, composite reliability, and Average Variance Extracted (AVE). All factor loadings surpassed 0.45, excluding three items (PU3=0.328, PU4=0.266, and PU5=0.241), which were eradicated to acquire a best fit measurement model, thereby providing testimony of convergent validity (Black & Babin, 2019). While the measurement achieved convergent cogency at the item level since all factor loadings were above 0.50, all composite reliability values for the latent variables exceeded 0.60, indicating a high level of internal consistency. Also, the convergent validity was shown by the fact that each value of AVE was higher than 0.50 (Bagozzi & Yi, 1988; Black & Babin, 2019). Also, Table 6 shows that all the correlations between pairs of constructs were less than the square root of the AVE estimates of the two constructs. This shows that the constructs can be distinguished from each other (Black & Babin, 2019). So, the measurements show that this study had both good convergence besides discriminant validity levels.

Table 6
Construct correlations

Constructs	PU	PEoU	TR	SI	TEL	BI	DP	AX
PU	**0.96**							
PEoU	0.930	**0.95**						
TR	0.773	0.433	**0.98**					
SI	0.341	0.200	0.300	**0.90**				
TEL	0.591	0.100	0.340	0.881	**0.90**			
BI	0.541	0.340	0.790	0.890	0.865	**0.93**		
DP	0.720	0.520	0.330	0.895	0.890	0.901	**0.82**	
AX	0.107	0.680	0.160	0.862	0.888	0.911	0.729	**0.86**

Note: Diagonal elements are square roots of the average variance extracted for each of the ten constructs. Off-diagonal elements are the correlations between constructs.

4.2.2. Structural Model

To examine the study hypotheses, SEM with Amos 20 was run. The results indicated that perceived usefulness, perceived ease of use, trust, social influence, and telepresence positively and significantly affected behavioral intention; therefore, hypotheses 1, 2, 3, 4, and 5 were accepted. Also, depression and anxiety have positively and significantly impacted behavioral intentions, so H6 and H7 were both accepted. Moreover, the coefficient of determination (R^2) for the endogenous research variables for behavioral intention, depression, and anxiety was 0.660, 0.640, and 0.604, respectively, which indicates that the model does consider the difference of the suggested model. Table (7) offers the results.

Table 7
Results for the theoretical model

Research Proposed Paths	Coefficient Value	t-value	p-Value	Empirical Evidence
$H_{1:}$ PU → BI	0.181	11.472	0.000	Supported
$H_{2:}$ PEoU → BI	0.111	3.185	0.001	Supported
$H_{3:}$ TR → BI	0.490	6.435	0.000	Supported
$H_{4:}$ SI → BI	0.471	32.022	0.000	Supported
$H_{5:}$ TEL → BI	0.351	11.472	0.000	Supported
$H_{6:}$ BI → DP	1.150	43.178	0.000	Supported
$H_{7:}$ BI → AX	1.106	40.017	0.000	Supported

4.3. Moderation Effects

Hypotheses H8-H14 claimed that there is a noteworthy variance in the respondent's behavioral intention as a result of the relative age, relative gender, relative educational level, relative marital status, relative time spent on the internet, social media venue, and relative internet experience. Table 8 shows the outcomes of the ANOVA test, which show that there is a noteworthy variance in the respondents' behavior intentions based on their relative age, relative education level, relative marital status, relative time spent on the internet, relative social media venue, and relative internet experience.

Table 8

ANOVA results

Variable		Sum of Squares	Df	Mean Square	F	Sig.
Behavioral intention is attributed to *relative age*.	Between Groups	139.293	3	46.431	172.767	0.000
	Within Groups	281.112	1046	0.269		
	Total	420.405	1049			
Behavioral Intention attributed to *relative educational level*	Between Groups	76.354	4	19.088	57.978	0.000
	Within Groups	344.051	1045	0.329		
	Total	420.405	1049			
Behavioral Intention attributed to *relative marital status*	Between Groups	49.890	2	24.945	70.489	0.000
	Within Groups	370.515	1047	0.354		
	Total	420.405	1049			
Behavioral intention is attributed to the *relative time spent on the internet.*	Between Groups	186.044	4	46.511	207.389	0.000
	Within Groups	234.361	1045	0.224		
	Total	420.405	1049			
Behavioral Intention attributed to *relative social media venue*.	Between Groups	206.011	7	29.430	143.037	0.000
	Within Groups	214.394	1042	0.206		
	Total	420.405	1049			
Behavioral Intention attributed to the *relative internet experience*	Between Groups	40.222	2	20.111	55.384	0.000
	Within Groups	380.183	1047	0.363		
	Total	420.405	1049			

The outcomes of the T-test, revealed in Table 9, showed a significant difference in behavioral intention that can be attributed to relative gender. That goes for females more than males.

Table 9
T-test results

		Relative Gender: Male			Relative Gender: Female				
Variable	N	Mean	Std. Dev.	N	Mean	Std. Dev.	T	df	Sig.
BI	533	4.5056	0.60131	517	4.7500	0.64154	6.364	1038.604	0.000

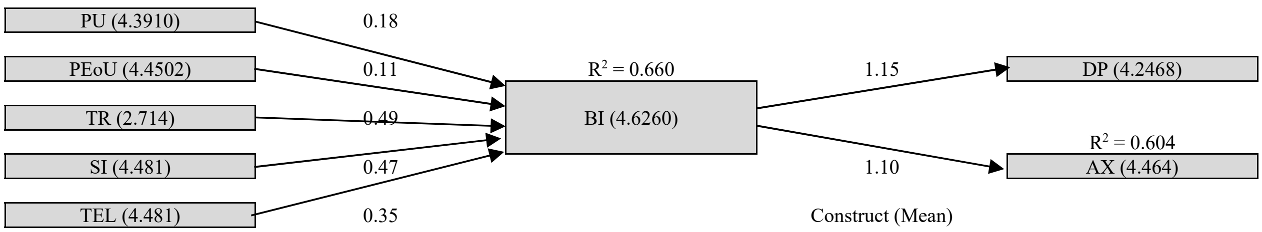

Fig. 2. SEM results of the proposed model**.**

4. Machine Learning Techniques - Validation & Prediction

This study estimates five machine learning (ML) methods for analyzing data and producing the desired output (Abu-Taieh et al., 2022d; Alkhawaldeh, 2021; Alkhawaldeh et al., 2022; Pallant, 2020). The methods used include “Artificial Neural Network” “ANN” (Da Silva et al., 2017), “Linear Regression” (Yao & Li, 2014) , “Sequential Minimal Optimization algorithm” for Support Vector Machine “SMO” (Platt, 1998), Bagging with the “REFTree model” (Breiman, 1996), and “Random Forest” (Tasin & Habib, 2022). These techniques are applied to study the impact of telepresence on social media on depression and anxiety. The “Artificial Neural Network” “ANN” adjusts its weights and biases to minimize the divergence between foretold and real output values through the back-propagation method. Linear Regression uses a polynomial function with weighted coefficients to predict the output based on the target labels and updates these coefficients during the training phase. Support Vector Machine (SVM) uses the “Sequential Minimal Optimization” “SMO” algorithm to optimize the weighted vectors of the model. Bagging creates multiple decision tree models using random subsets of the training data, and the average of these trees is used as the final prediction. “Random Forest” “RF” is a collection of decision tree models created with random subsets of training data and attributes. The average of these trees is used as the final prediction. The 10-fold cross-validation technique is a method to measure the model's ability to predict desired values. It involves dividing the data set into 10 parts, using 9 of them for training and 1 for testing, and repeating this process 10 times. The average performance is then used to evaluate the model. This approach helps to prevent overfitting by using the entire dataset for training and testing and reducing the chances of a model that performs well on the training data but poorly on the test data.

4.1 ML Results and Discussion

To study the factors that contribute to depression and anxiety in adults who use social networks, an automatic classification model is needed to predict these factors. Machine Learning techniques analyze inputs (or independent variables) and create a model for predicting the dependent variables. We will conduct experiments on three datasets (1) dataset1, which includes PU, PEoU, TR, SI, and TEL factors as inputs and the BI variable as output; (2) dataset2, which includes BI as input and DP as output; and (3) dataset3, which uses BI as input and AX as the dependent variable.

The experiment results are presented in Fig. 3 and Fig. 4 using “Mean Square Error” “MSE” and R-squared (R^2) as evaluation systems of measurement. The R^2 and “MSE” values are shown on the y-axis, and the models are presented on the x-axis. R^2 statistic indicates the influence of independent variables on the dependent variable, while the MSE measures the average difference between a model's predicted and actual output values. Tree-based approaches performed well, with R^2 values of 92%, 88%, and 87% for Bagging “REPTree” and Random Forest on Dataset1, Dataset2, and Dataset3, respectively. The results suggest that six factors are effective for predicting the BI variable, the BI to DP, and the AX variables. SMO and linear regression models also produced good results with errors of less than 2%. The MSE metric of tree-based and other techniques showed errors of less than 20% to 6%. Therefore, we conclude that Machine Learning techniques are effective to predict the BI variable and other two factors, depression and anxiety in Social Networking, particularly in Jordan.

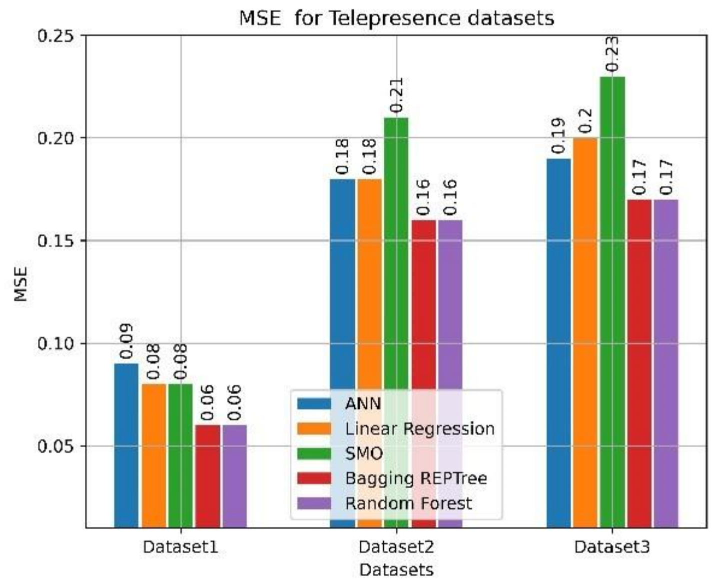

Fig. 3. ML experimental results using Mean Square Error (MSE) as evaluation metrics

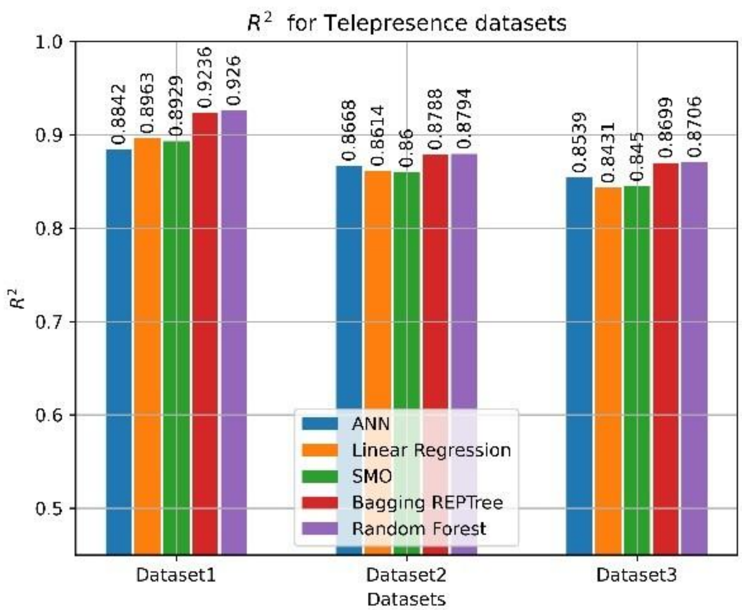

Fig. 4. ML experimental results using R2 as evaluation metrics.

5. Discussion and implications

In this section, the paper presents the discussion and findings, practical and theoretical implications, limitations and future research suggestions, and the conclusion of this research.

(45.8%) of the respondents used the SNS for 3 hours, while (48.7%) used it for more than 5 hours. Among the independent variables, the SI and TEL were ranked highest, first and second, respectively, while TR was ranked least, with a mean of 2.7141. Further, the dependent variables' anxiety outranked depression with a standard of (4.4643).

The construct perceived usefulness (PU), measured by 5 items, PU2 and PU4, was the highest according to the mean. Item (PU2) pertains to connectivity to others, while item (PU4) pertains to the connectivity of friends and family. PU had a strong positive correlation with all constructs except Social Influence (SI) and Anxiety (AX). The PU's positive influence on behavioral intention (BI) was supported in this study, as shown in table 7, with a coefficient value of (0.181). As such, the claim was supported in other studies like Suki & Ramayah (2012) and Hansen et al. (2018) disagreed with Dixit & Prakash (2018).

The construct perceived ease of use (PEoU), measured by 4 items, PEoU2 and PEoU3, was the highest according to the mean. PEoU2 pertains to clarity and understandability, while PEoU3 pertains to ease of use. PEoU strongly correlates with dependent constructs like depression (DP), anxiety (AX), and PU. Yet, moderate correlation between TR and BI and a weak correlation with SI and TEL. The PEoU positive influence on BI was supported in this study, as shown in table 7, with a coefficient value of 0.111. As such, the claim was supported in other studies like Dixit & Prakash (2018), Suki & Ramayah (2012), and Hansen et al. (2018).

Trust (TR) had a strong correlation with behavioral intention (BI) and perceived usefulness (PU), also a moderate correlation with social influence (SI), telepresence (TEL), depression (DP), and perceived ease of use (PEoU). On the other hand, TR had a weak correlation with anxiety (AX). As shown in table 7, the positive influence of TR on BI was supported in this study, as shown in the coefficient value (0.490). As such, the claim was supported in other studies (Baabdullah, 2018; Hansen et al., 2018; Tiwari et al., 2021; Alalwan et al., 2017; Alalwan et al., 2018)

The items of constructs Social Influence (SI), Telepresence (TEL), and Behavioral Intention (BI) were all scored high according to the mean. Social Influence (SI) had a strong correlation with Telepresence (TEL), Behavioral Intention (BI), Depression (DP), and Anxiety (AX). SI has a moderate correlation with perceived usefulness (PU) and trust (TR) and a weak correlation with perceived ease of use (PEoU). The SI positive influence on BI was supported in this study, as shown in table 7, with a coefficient value (0.470). As a result, the claim was supported by other studies (Pentina et al. 2012; Usman & Okafor ,2019).

Telepresence (TEL) had a strong correlation with behavioral intention (BI), depression (DP), anxiety (AX), perceived usefulness (PU), and social influence (SI). In contrast, they have a moderate correlation with trust (TR) and a weak correlation with perceived ease of use (PEoU). Also, the (TEL) positive influence on BI was supported in this study, as shown in table 7, with a coefficient value of (0.351). As such, the claim was supported in other studies like Kwak et al. (2014), Pelet et al. (2017) and Lee et al. (2020).

Behavioral Intention (BI) had a strong correlation with Depression (DP), Anxiety (AX), Perceived Usefulness (PU), Trust (TR), and social influence (SI), and a moderate correlation with perceived ease of use (PEoU). BI positive effect on DP and AX was supported in this study, as shown in table 7, with coefficient values (1.150) and (1.106), respectively. As such, the claim was supported in other studies like Huang (2022), McCord et al. (2014), Seabrook et al. (2016), and Merrill et al. (2022).

Depression (DP) was measured by 6 items; DP3, DP4, and DP5 were the highest according to the mean. DP3 asked about interest, DP4 asked about loneliness, and DP5 asked about being upset when not using SNS. The results show that the latent variable DP had a strong correlation with perceived usefulness (PU), perceived ease of use (PEoU), social influence (SI), telepresence (TEL), and behavioral intention (BI), and a moderate correlation with trust (TR).

In Anxiety (AX), all 4 items were high, where AX2 was the highest according to the means. The latent variable anxiety (AX) had a strong correlation with perceived ease of use (PEoU), social influence (SI), telepresence (TEL), behavioral intention (BI), and depression (DP), but a weak correlation with perceived usefulness (PU) and trust (TR).

As stated in H8, age significantly influences behavioral intention (BI). This agrees with the findings of Lu & Yang, (2014), Suki & Ramayah (2012), Pfeil et al. (2009), Zaphiris et al. (2007), Blank & Lutz (2017) and disagrees with the findings of Leong et al. (2013).

Education level and marital status influence Behavioral Intention (BI) stated in H10 and H11 agrees with the findings of Blank & Lutz (2017) and disagrees with the results of Leong et al. (2013). As shown in Table 8, there is a significant difference according to different groups.

As predicted, gender positively influenced behavioral intention (BI) towards females, as stated in H9. The female gender had a mean of (4.75) while the male gender had a mean of (4.5056). Table 9 shows the proof with corresponding numbers. As such, the findings agree with the results of Leong et al. (2013) and Blank & Lutz (2017) and disagree with the conclusions of the study proposed by Faiola et al. (2013).

As expected, behavioral intention (BI) was affected by time spent on the internet, as stated by H12, which agrees with the findings of Tourinho & de Oliveira (2019) and Sanz-Blas et al. (2019). This finding is reflected in table 8.

As projected, behavioral intention (BI) was affected by favorite social media networks, as stated by H13, which agrees with the findings of Chuang et al. (2017), Blank & Lutz (2017), McCord et al. (2014) and Sanz-Blas et al. (2019). This finding is reflected in table 8. As anticipated, behavioral intention (BI) was affected by internet experience, as stated by H14, which agrees with the findings of Campisi et al. (2015), Morris & Venkatesh (2000) and Trocchia & Janda (2000).

6.1. Theoretical and practical implications

Researchers, practitioners, medical professionals, psychological professionals, and educators can use this research as a plinth for future study and research. Furthermore, SNS developers can use the study findings as part of their social responsibilities when designing and developing new SNSs. As part of the SNSs, a developer may include a timer or alert for the user when spending too much time on the SNSs or showing signs of anxiety and depression. A psychological parameter may be researched and developed so that a user with depression or anxiety symptoms can be shown. Such findings can be used to educate people about the negative impact of SNSs on people. Hence, warning people about the negative side of SNSs. Medical and psychological professionals must be aware of such a negative reflection of SNS on humans. Raising mental health awareness was recommended by McCrae (2019). With more people becoming aware of mental health problems and seeking help, doctors may be more likely to diagnose and treat them. This could have the effect of lowering the diagnostic threshold.

6.2. Limitations and directions for further research

Depression and anxiety have negative connotations, especially in Jordan. Hence, the researchers faced many challenges in collecting information regarding this topic. Also, social media is taken lightly. Therefore, people don't consider their association with depression and anxiety. SNS environments are changing; different SNSs appear now and then, while different SNSs appear and fall, so it is challenging to study the effect of one SNS on behavioral intention. As for future studies, a more detailed and in-depth study must be conducted for the trust (TR) construct due to the low mean and high loading factor. The role of gender in depression and anxiety is also investigated. Telepresence (TEL) and its correlation with time spent on the internet should be investigated.

6.3. Conclusion

The study's sample size was representative since the (R) squared was above 0.6). Furthermore, according to the respondents, the study is reliable in its findings.

All the independent constructs, as expected, did influence BI. The hypothesis about the independent constructs (H1-H5) was supported by PU, PEoU, TR, SI, and TEL. Hence When using SNSs, perceived usefulness, perceived ease of use, trust, social influence, and telepresence all influence behavioral intention. Also, the respondents' depression and anxiety were affected by their plans to act, which supports hypotheses H6 and H7.

There is a significant difference in the respondent's behavioral intention due to the relative age, relative gender, relative educational level, relative marital status, relative time spent on the internet, social media venue, and internet experience.

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