Modelling the Mental Health of Social Media Users Among University Students

Geoffrey Mayoka Kituyi

Submitted to: JMIR Mental Health
on: February 24, 2025

Table of Contents

Modelling the Mental Health of Social Media Users Among University Students

Geoffrey Mayoka Kituyi[1]

[1]Computer Science and Engineering Computing and Informatics Makerere University Business School Kampala UG

Corresponding Author:
Geoffrey Mayoka Kituyi
Computer Science and Engineering
Computing and Informatics
Makerere University Business School
Kampala
Kampala
UG

Abstract

The purpose of this study was to develop and test a model that can be used to promote the learning of positive mental health amongst social media users while engaged on social media platforms.

A cross-sectional research design was adopted with a positivist epistemology. Data were collected from 450 social media users Uganda, Cameroon and Nigeria. Descriptive statistics, confirmatory factor analysis and structural equation modeling methods were used to analyze data.

The proposed model was tested and found to be fit. The obtained =8.653 is below 20, /DF=1.442, P=.194 is above the recommended minimum of 0.5. The GFI=.993, AGFI=.968, NFI=.983, RFI=.940, IFI=.995, TLI=.981, and CFI=.994 were all above the threshold of 0.9. The obtained RMSEA of .035 was also far below the recommended maximum threshold of 0.08 for a model to be fit. Based on these indices, we conclude that the proposed model explains mental health of social media users.

(JMIR Preprints 24/02/2025:73051)
DOI: https://doi.org/10.2196/preprints.73051

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?
✔ **Please make my preprint PDF available to anyone at any time (recommended).**
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
No, I do not wish to publish my submitted manuscript as a preprint.
2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?
✔ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**
Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http
No. Please do not make my accepted manuscript PDF available to anyone.

Original Manuscript

Modelling the Mental Health of Social Media Users Among University Students

Abstract

The purpose of this study was to develop and test a model that can be used to promote the learning of positive mental health amongst social media users while engaged on social media platforms.

A cross-sectional research design was adopted with a positivist epistemology. Data were collected from 450 social media users Uganda, Cameroon and Nigeria. Descriptive statistics, confirmatory factor analysis and structural equation modeling methods were used to analyze data.

The proposed model was tested and found to be fit. The obtained χ^2 =8.653 is below 20, χ^2 /DF=1.442, P=.194 is above the recommended minimum of 0.5. The GFI=.993, AGFI=.968, NFI=.983, RFI=.940, IFI=.995, TLI=.981, and CFI=.994 were all above the threshold of 0.9. The obtained RMSEA of .035 was also far below the recommended maximum threshold of 0.08 for a model to be fit. Based on these indices, we conclude that the proposed model explains mental health of social media users.

1. Introduction

Social media (SM), which have gained prominence and wide usage over the past decade, are online applications and platforms that enable individuals to exchange information in close groups of interest or to the wider online community [1]. According to [2], SM encompasses all electronic platforms “through which users create and engage in online communities to share ideas, personal messages, and other information”. These media provide powerful features that allow users to create customized content for exchange. Users who cannot create their own content have a variety of readily available online content which they can use and share. Many SM platforms in existence today offer a multiplicity of services, ranging from simple text exchange platforms to high-end platforms that allow exchange of multimedia forms of data such as text, voice, videos among others. Most of SM interactions are instant, very affordable and can be accessed even using a basic internet enabled phone. The media are being used for business and leisure [3; 4]. The most popular SM in use today include Facebook, YouTube, Twitter, Skype, WordPress, Wikipedia, Instagram, Bobo, Naijanet and Baraza among others. Facebook that launched in the early 2000s is now the leading SM website with over 1.44 billion users [5], followed by WhatsApp with about 1 billion users [6] and Instagram with 300 million users [7], Skype 74 million users [8].

Behavioral scientist, psychologists and social learning scholars such as Bandura [9; 10; 11; 12] emphasize the influence of consuming information – whether textual, audio, or images on behavioral change. Given that SM platforms have abilities to store data so that it can be used in the future, they provide repeated consumption of the same information over a period of time. According to Bandura’s SCT, this leads to indirect learning (also known as delayed learning) – a form of learning that occurs over a period of time through observation [13]. Further, as earlier indicated, SM platforms provide easy access to information from actors and players in different aspects of life. There are celebrities, medical practitioners, religious leaders, students, teachers, political leaders, organizations, etc. These actors play an important behavioral dissemination role. They act as role models from whom new behaviors can be learned by users in their online communities. For example, a cancer hospital is able to offer counseling services to patients through a Facebook page [14]. Pharmaceutical corporations and NGOs promote condoms and other sexual reproductive products via SM [15; 16]. Cigarettes companies are able to market their products to the global online audience [17; 18]. Beer and other alcoholic beverage producers are able to market their products online via SM [19; 20] and prostitutes are also available and aggressively marketing their services via online SM platforms [21; 22; 23; 24]. Likewise, religious organizations offer services via online SM platforms [25; 26].

Broadly, studies such as [27] and [28] had been conducted to examine the role of SM as a health communication tool. Diminutive research focused on SM and Mental health. An extant literature assessment revealed few studies focusing of SM and health. For example, [29] conducted an experiment on the spread of behavior in an online social network of 1500 users and found that member learned new behaviors. Further, [30] found that SM played a great role in influencing behavior to closed as well as open SM online groups. Adewuyi and [31] conducted a desktop study on behavioral change using SM and called for strategic deployment of the technology for better results, while [32] conducted a study and concluded that SM were useful tools for health promotion and behavioral change. Important to note is that with the exception of Adewuyi and [31] which is a literature review study, all of these studies were conducted in western countries, specifically in the United States of America. Diminutive or no research has been conducted on the subject matter with a focus on Sub-Saharan Africa. The available literature on this region focuses mainly on telemedicine and e-health adoption and usage, which are generic in nature [34;35]. The current study therefore sought to close this eminent gap by examining the factors influencing mental health via SM and developing a model for understanding and guiding good mental health via the technology.

The aim of this study was to investigate the factors influencing Mental health via SM and to develop a model that can be used to promote positive mental health by SM users.

2. Social media and behavioral change

Over the past decade, SM platforms have become one of the key drivers of behavioral change [36]. The platforms provide an environment where information flows freely [37]. There are role models such as community leaders, political leaders, religious leaders, celebrities all over the SM platforms [38]. These role models send information that is readily available to the world. Information is easily received via SM and processed cognitively to influence behavior [39]. Consequently, new patterns of behavior are immerging globally, as the platforms have no boundaries [40; 41; 42]. A behavior that was predominant on one continent is now eminent on all the other continents.

Although there is a tendency for people in developed countries to learn some behavior from developing countries, the biggest influence has been behavior moving from the developed to underdeveloped countries. Many people, especially the youth perceive cultures, norms and beliefs of those in developed countries more superior and trendier compared to theirs. Hence, little is being exported from underdeveloped to developed countries, but rather from the developed to the underdeveloped. Consequently, SM users have embraced the cultural practices, norms and values of western countries. These are in terms of democracy, single spouse marriages, same sex marriages, religious beliefs, education, family values, and human rights among others. Therefore, it is apparent that SM plays a great role in influencing behavior.

In his study, [43] applied the SCT in trying to understand how mass communication and the media at large influenced behavior. Consequently, [43] argues that the mass media provides a symbolic form of communication that influences human thought, thereby affecting the behavior. SM platforms influence behavior in two ways; 1) media influence and 2) providing connection to social systems. Media influence promotes changes through provision of information, provision of an enabling environment for information sharing, provision of the motivational factors for behavioral change, and provision of the much-needed guidance for the users to implement learned behavior. Further [43] posits that the networks provided through media help to create linkages among various participants. This provides natural incentives necessary for behavioral change.

3. Theoretical underpinning of the study

3.1 Social Learning Theory

According to [44], studies on Social Learning Theory (SLT) started way back in the 1800s. The first proponent of eminent ideas of this theory was William James in 1890. Through his study titled “the social self”, [45] was the first scholar known to have laid the foundation for investigating individuals and the environment where they operated. In the 1900, Adler brought in the idea that individuals purposively behaved the way they did with the motivation of realizing some goals as cited by [44]. Further, [46] introduced the idea that cognition factors influenced behavior. Research shows that [47] were the first scholars to publish a paper on SLT in 1941. In this paper they argue that human behavior can be reinforced through the environment and also that humans are motivated internally. With all these developments leading up-to the end of 1950, several researchers had applied [47] social learning and imitation model. However, [44] notes that most of these studies centered on three themes namely; 1) learning through experience and observation; 3) modeling behavior based on identification (similarity and emotional attachment); 3) the probability of a person repeating a given behavior depended on the ultimate consequences. Further, [44] classified the consequences as either rewards or punishments. After the 1950s, more advanced theories were proposed by notable scholars including [48; 49] and Albert Bandura [12; 50]. Whereas [51] agrees that several theories have been advanced over the years to investigate behavioral change and learning, he posits that the various theories have differences in understanding of human nature in terms of motivation for behavioral change.

3.2 Social Cognitive Theory

Developed by [13], the Social Cognitive Theory (SCT) has its roots in the SLT (SLT) by the same author in 1961 [13; 12]. The theory tries to understand the learning process that takes place in humans and animals through observing others. SCT has been widely used in social research aimed at predicting behavioral change in individuals and has recently become a benchmark to technology acceptance theories that examine computer acceptance and usage [52; 53].
According to [54] the SCT of [13] posits that whereas the environment influences changes in behavior, a person's behavior also influences changes in the environment, hence the "reciprocal determinism" [13]. Reciprocal determinism explains the situation where "the world and the behavior of persons are mutually caused" [54; 13]. The theory proposes three reciprocal constructs that interact to cause behavioral change. These include personal factors also known as Cognitive Factors (CF), environmental factors and behavioral factors.
As earlier indicated, [13] SCT puts emphasis on reinforcement and observation as key drivers for learning and behavior change. The ultimate change in behavior will be influenced by the role models observed - hence credence is given to role models. Role models are those actors whose behavior is learned and or imitated by the subject. These can be teachers, parents, peers, or even outstanding people in the society such as political leaders, TV personalities and celebrities among others.
The strengths of the social learning and cognitive theories are; 1) they show that learning is a process that takes time and not an event, 2) role models are key in learning and unlearning behavior through observation and mimicking, 3) the three types of reinforcement (direct, vicarious and self) show the different ways an individual processes learning information, and 4) they cater for indirect learning- a form of learning outside the classroom.

3.3 Theoretical gaps of social learning and cognitive theories

In his study [11] has direct reinforcement, vicarious reinforcement, self-reinforcement, role modeling, and self-efficacy but lacks ILC, ELC, behavioral potential, expectancy, reinforcement value and psychological situation and yet these are key in addressing behavioral change as seen in [48]. Further, [11] does not ably address reciprocal determinism, CF, environmental factors, behavioral factors, OE and SR seen in [13]. Age and gender are also missing in this theory – yet these have been identified as moderators of CF and behavioral change [55; 56; 57; 58; 59;60; 61].

On the other hand, Rotter's 1966 theory covers both internal and ELC, behavioral potential, expectancy, reinforcement value and psychological situation. However, the theory does not address salient issues such as direct reinforcement, vicarious reinforcement, self-reinforcement, role modeling and self-efficacy that had been advanced by [11] as important consideration for understanding the learning of human behavior. In addition, Rotter's theory is faulted on addressing cognitive, behavioral and environmental factors of learning [13]. It is also apparent that role modeling, reciprocal determinism, OE, self-efficacy and SR are all missing [13]. Just like Bandura, [48] did not address age and gender in behavioral influence [55; 56; 57; 58; 59;60; 61].

Lastly, a close examination of Bandura's 1986 SCT reveals that the theory adequately addresses role modeling, reciprocal determinism, CF, environmental factors, behavioral factors, OE, self-efficacy and SR. However, [13] SCT does not address age and gender issues [55; 56; 57; 58; 59;60; 61]. Further, [13] ignored what he had proposed in [11] as important elements of behavioral change.

These include direct reinforcement, vicarious reinforcement and self-reinforcement. It is also evident that locus of control (internal and external), behavioral potential, expectancy, reinforcement value and psychological situation are lacking in this theory. Table 3 presents results from the matrix analysis.

4. Research methods

4.1 Ontological approach

Ontology is a major branch of philosophy that aims to study what is in existence, or what will exist. It is derived from the Greek word “onto” that means “being” and “logos” that means “science” [62]. It can be perceived in a philosophical sense or in the computational sense [63]. This study looks at ontology from the philosophical perspective – which is “the science of what is, of the kinds and the structures of objects, properties, events, processes relations in every area of reality” [64]. Lawson [62] adds that ontology is the study of being or the science of being a thing or something. In computer science, ontology can be used to study the interrelations between objects. There are mainly two branches of ontology; positivism / positivist ontology and subjectivism or subjectivist ontology.

The positivism ontology assumes a single reality that is independent of the researcher. It allows the researcher to conduct the study in a neutral manner. On the other hand, subjectivism ontology assumes existence of multiple realities such that the researcher has to engage it in a value-based approach. This study used positivist ontology - also known as objectivism ontology which adopts a quantitative research approach.

4.2 Research design and epistemology

The study adopted a cross-sectional quantitative survey, where data were collected and analyzed quantitatively at a point in time (De Lisle, 2016; Bulsara, 2016; Sedgwick, 2014).
Further, in order to create knowledge on SM and Mental health while ensuring that the researcher was independent of the study, a positivist epistemology was adopted.

4.3 Data collection and analysis

The study aim was to develop and test a model that can be used to promote good mental health while engaged on social media platforms. A cross-sectional research design was adopted with a positivist epistemology. Data were collected from 450 social media users Uganda, Cameroon and Nigeria. Descriptive statistics, confirmatory factor analysis and structural equation modeling were used to analyze data.

The proposed model was tested and found to be fit. The obtained χ^2 =8.653 is below 20, χ^2 /DF=1.442, P=.194 is above the recommended minimum of 0.5. The GFI=.993, AGFI=.968, NFI=.983, RFI=.940, IFI=.995, TLI=.981, and CFI=.994 were all above the threshold of 0.9. The obtained RMSEA of .035 was also far below the recommended maximum threshold of 0.08 for a model to be fit. Based on these indices, we conclude that the proposed model explains mental health of social media users.

4.4 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is a statistical procedure that is used to test the hypothesized set of observed variables and confirm if they measured the latent variable [65]. CFA in social sciences is used to determine if the observed measurement variables are in-line with the researcher’s hypothesized measurement variables. CFA for this study was done using Analysis of a Moment Structures (AMOS), which is an add-on for the Statistical Package for the Social Sciences (SPSS) software. During the analysis, Standardized path estimates, also known as Beta are used to eliminate observed variables that have weak relationships with their latent variables

In order for a measurement model to be fit, it must meet the goodness of fit acceptable indices. For example, the Nonormed Fit Index (NNFI), also known as Tucker Lewis index (TLI) which is used to measure for parsimony by comparing degree of freedom for observed variables to the degrees of freedom of the hypothesized variables [66]. Other indices include the Comparative Fit Index (CFI) and Root Mean Squared Approximation of Error (RMSEA), Chi-square (X^2) and P-values. CFI is used to control for sample errors [66], while RMSEA is used to measure the differences in covariance matrices per degree of freedom for the hypothesized and observed model variables [71;72]. On the other hand, the Chi-square (X^2) is the sum of squared correlations between model matrices and P-value is a statistical value used to determine whether the null hypothesis is significantly different from the proposed model. Chi-square (X^2) is used concurrently with X^2/DF and P value.

Generally, a model is fit if X^2/D.F.<=3 and P>0.5 [73]. The model should also have NNFI>0.9, TLI>0.9, CFI > 0.9 and RMSEA < 0.08 [66; 67; 68; 69].

4.5 Structural Equation Modeling

Structural Equation Modeling (SEM) is a powerful scientific analysis tool that helps to confirm factors measure individual variables while at the same time build Structural Equation Models for testing research hypotheses [66]. SEM helps to show the relationships between multiple constructs in paths as well as inferential statistics [66; 68] and is most appropriate for testing of hypothesis with prior a model.

SEM was chosen because of its ability to test for mediation, moderation as well as the predicting power of independent variables to the independent variable. Further, the sample taken in this study was appropriate for the use of SEM, given that the required minimum sample is 200. Hence, with a sample of 450 SEM would compute results with a good statistical power [70]. SEM uses the following indices to analyze data.

The Chi-square (X^2) is the sum of squared alterations between model matrices. Its function is $\chi 2 = F*(N-1)$ - where F is the value of the fitting function and N is the sample size. The Chi-square (X^2) is used to measure actual and estimated model matrices. A low X^2 implies nonsignificance in difference hence the model is fit. A high X^2 implies a significant difference between actual and predicted models. The Chi-square and degree of freedom (X^2/D.F.) ration should be less <=3 [73]. Chi-square is very sensitive where the sample size is greater than 200, making it inappropriate for model evaluation. Where the sample is very high there is need to look at other indices [66; 69]. Nonormed fit index (NNFI), also known as Tucker Lewis index (TLI) is used to compare the model's fit to a "nested baseline or null model" and also measures parsimony by comparing df of proposed model to df of null model [66]. NNFI should be >0.9 for the model to fit.

Comparative fit index (CFI) is a noncentrality measurement index used to control for the errors due to a very low or high sample size [66]. CFI of 0.9 indicates good model fitness.

Root mean squared approximation of error (RMSEA) is used to measure the differences in covariance matrices per DF for the proposed and observed model (Garver & Mentzer, 1999; Steiger, 1990). RMSEA<0.05 is deal, while RMSEA<=0.08 is acceptable, while RMSEA above 0.08 is mediocre fit.

P-value is a statistical value used to determine whether the null model is significantly different from the proposed model. It is used to reject the null hypothesis that X^2=0. A low p-value indicates significance, while a high p-value indicates that there is no significance. Hence, for model good fitness, p-value should be high – indicating there is no significant difference between the null and proposed models [66; 67].

Standardized path estimates help to show the strength of relationships between model variables. Higher Standardized path estimates are desirable. A Standardized path estimate below 0.2 means the relationship between variables is weak and adds little value to the model. The ideal path estimate should be 0.3 and above- however, 0.2 is acceptable [68].

4.6 Conceptual framework

The conceptual framework is based on SCT of Albert Bandura which posits that CF play a big role in causing behavioral change through the process of reciprocal determinism with other constructs [13]. In addition, we borrow the constructs of Internal Locus of Control (ILC) and External Locus of Control (ELC) that were identified as important factors in influencing mental health by Rotter in his SLT [10]. Another hypothetical addition to the study is the role of age in moderating behavioral learning process as had been proposed by researchers in the field of psychology. In this study, Age Sensitivity (AS) is hypothesized to moderate the relationship between CF and Self-Regulation (SR). Individuals' level of AS either increases or reduces the influence of their CF on SR in the behavioral learning process. Further, studies by [13], and [10] show that Outcome Expectations (OE) or Expectancy for the case of [10] influence behavior through increasing or decreasing the learner's locus of control. However, [10] cautions that OE (Expectancy) is relevant only in a responsive environment. Hence, in this study, we hypothesize that OE influence ELC of SM users. Individuals with high expectations will be more open to adopt new observed behaviors from elements in the environment and the reverse is true.

The other constructs hypothesized in this study are SR [13] and Behavioral Intention (BI) [74]. In this study, CF positively influence SR while SR is also hypothesized to have a positive influence on the ELC as well as Mental health (MH). On the other hand, BI is hypothesized to positively influence MH as well as mediate the relationship between ILC and MH. Figure 1 presents the conceptual framework.

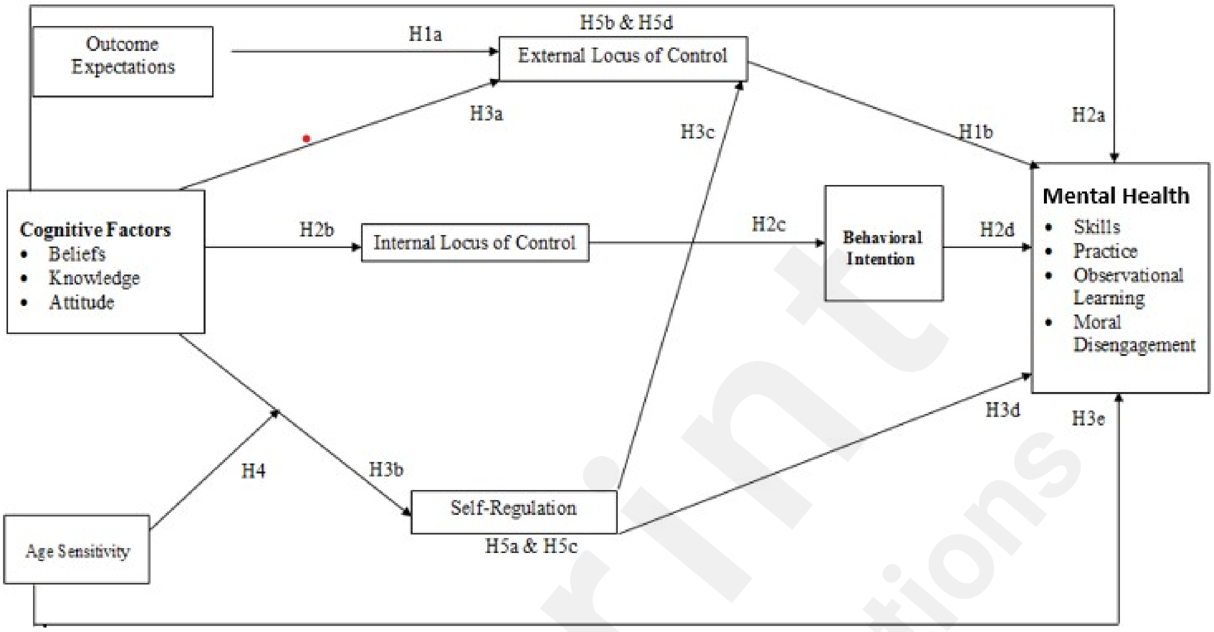

Figure 1: Conceptual framework adapted from literature of [11; 10;13; 74]

5. Findings

5.1 Demographics

Data were gathered about respondents' gender and age. The data were analyzed using frequencies and percentages. Findings revealed that most respondents were male (Freq=222, 62%). Only 136 representing 38% were female respondents. In terms of age, most respondents were 30-39 years old (freq=174, 49%). This was followed by age group 20-29 years (freq=125, 35%), and 40-49 years (freq=53, 15%). Only 4 respondents constituting 1% and 2 respondents constituting 0.6% were below 20 years and 50 years and above respectively.

5.2 Confirmatory factor analysis results

Cognitive Factors

CF variable had three hypothesized constructs namely; 1) Beliefs, Knowledge and 3) Attitude. Beliefs had 6 of six measurement items; Knowledge and Attitude had 4 items each. CFA was conducted to validate these constructs and factors that measured CF.

Out of the 3 constructs, only Beliefs and Knowledge were found to measure CF. Beliefs had 4 items retained, while Knowledge retained 3. Through a systematic elimination method, those factors with low factors loadings were deleted from the model. On the other hand, those items whose error terms exhibited high modification indices and covariances were regressed. The observed variable was significantly different from that hypothesized. This was because Attitude as a construct was dropped from the model in addition to a few measurement items that were dropped from the retained constructs.

Results indicated that the model was not fit based on the Chi-square obtained and a P-value of 0 (χ^2=38.508, DF=11, P=.000, χ^2/DF=3.501). However, most of the measurement indices indicated that the mode was fit. For instance, GFI=.971, AGFI=.925, NFI=.968, RFI=.939, IFI=.939, TLI=.956, and CFI=.977 were all above the threshold of 0.9. The RMSEA=.08, also met the threshold of 0.8.

Further, we observed that the Average Variable Extracted (AVE) for this variable was 0.588, which was above the required 0.5. This implies that there was convergent validity, i.e. the measurement items for each construct converged to measure their respective constructs. This was supported by the fact that each retained observed variable had a significant relationship with its parent construct as all P-values were below 0.001.

The obtained squared correlation of the two constructs (R^2) was 0.38. This was below the obtained AVE which was 0.588. This finding implied that there was discriminant validity between the two constructs of Beliefs and Knowledge. Each of these two was unique and its measurement items measured only that construct.

Based on the above findings, it was concluded that Beliefs with its 4 measurement variables and Knowledge with its 3 measurement items adequately measured CF.

Internal Locus of Control

The observed variable ILC (ILC) had 7 hypothesized measurement items. However, CFA results retained 5 measurement variables. The observed variable in this model was not significantly different from that hypothesized. This was because only 2 measurement items were dropped.

The model for ILC was fit because all the measurement indices exhibit great goodness-of-fit. The Chi-square χ^2=.769 at 3 degrees of freedom with χ^2/DF=.256 at P=.857 indicated good fitness.

More indices including GFI=.999, AGFI=.996, NFI=.999, RFI=.997, IFI=1.003, TLI=1.010, and CFI=1.000 were all indicators of good model fitness. The RMSEA=.000, which was far below the threshold of 0.8. It was on this basis that ILC was confirmed as one of the study variables.

External Locus of Control

ELC had 8 hypothesized measurement factors out of which only 4 were retained in the CFA. The observed variable in this model was significantly different from the one hypothesized in the study. This was because half of the measurement factors were dropped for having weak loadings. The statistics for ELC reveal that model was fit (χ^2=.279, DF=1, P=.597, χ^2/DF=.279). The Chi-square was below 20, χ^2/DF was less than 3, and P-value was above 0.5 indicating good model fit. In addition, GFI=1.000, AGFI=.996, NFI=1.000, RFI=.998, IFI=1.001, TLI=1.005, and CFI=1.000 were all above the threshold of 0.9. The RMSEA=.000 was below the required maximum threshold of 0.8. Therefore, this model was found to be fit and used to measure ELC.

Further, we observed that the AVE for this variable was 0.69, which above the required 0.5. This revelation, coupled with all significant P-values between each factor and ELC, indicated that there was convergent validity. In other words, all the measurement items converged to measure ELC.

Self-Regulation

SR had a totla of 16 measurement variables out of only 7 were retained in the CFA. Regressions were done on all error terms because they had high covariances. The observed variable in this model was significantly different from the one hypothesized in the study because more than half of the measurement factors were dropped for having weak factor loadings.
The statistics for ELC revealed that the model was fit (χ^2=22.467, DF=5, P=.000, χ^2/DF=4.493). The Chi-square was above 20, χ^2/DF was above 3, and P-value is below 0.5 indicating bad model fit. Despite this, all other goodness of fit indices indicated that the model was fit. The GFI=.983, AGFI=.904, NFI=.988, RFI=.950, IFI=.991, TLI=.960, and CFI=.991 were all above the threshold of 0.9. The RMSEA=.099 was slightly above the required maximum threshold of 0.8. Given the fact that this study had a high sample of 358, even if the RMSEA was above 0.8, this model was fit since other goodness of fit indices indicated good model fitness.
The AVE for this variable was 0.535, which was above the required 0.5 and all P-values were significant at P<0.001. This implied that there was convergent validity. All the retained variables converged to measure SR.

Age Sensitivity

This variable had 6 hypothesized factors out of which 4 items were retained to explain AS. CFA findings were not significantly different from the hypothesized variable AS since only 2 factors were dropped. Hence, the retained factors were confirmed to measure AS.
Some findings indicated that the model was not fit. The statistics obtained including χ^2=3.816 and χ^2/DF=3.816 at P=.051 and RMSEA=.089 did not meet the required thresholds for good model fit. However, the remaining measurement indices indicated that the mode was fit. For instance, GFI=.995, AGFI=.947, NFI=.997, RFI=.979, IFI=.997, TLI=.985, and CFI=.997 were all above the threshold of 0.9. Given that the study sample of 358 was way above the

recommended sample of 200 for SEM, this model can be accepted. This is because chi-square is sensitive to samples – such that once the sample is above 200, it may not be very reliable (Kline, 1998).
Further, we observed that the AVE for this variable was 0.737, which was above the required 0.5 and also that all observed variables had significant relationships with the unobserved variable at P<0.001. This implied that there was convergent validity, i.e. the observed variables converged to measure their unobserved variable AS.

Outcome Expectation

This variable OE had 7 hypothesized factors. CFA results indicated that 5 items were retained to measure OE. Four error terms were found to have high covariances and were regressed in order to minimize the unexplained errors between those that were highly related.
CFA findings did not significantly differ from the hypothesized factors measuring OE since only 2 factors were dropped. Hence, the retained factors were confirmed to measure OE.
The first set of results suggested that the model was not fit. Statistics obtained including χ^2=6.253 and χ^2/DF=3.126 at P=.044 did not meet the required thresholds for good model fit [66; 67; 68]. However, the remaining measurement indices indicated that the mode was fit. For instance, GFI=.993, AGFI=.950, NFI=.997, RFI=.985, IFI=.998, TLI=.990, and CFI=.998 were all above the threshold of 0.9. Given that the study sample of 358 was way above the recommended sample of 200 for SEM, this model can be accepted. This is because chi-square is sensitive to samples – such that once the sample is above 200, it may not be very reliable [73]. Further, the RMSEA was .077, which is below 0.8. Hence the model was fit.

The AVE for this variable was 0.731, which is above the required 0.5 and also that all observed variables had significant relationships with the unobserved variable at P<0.001. This implied that there was convergent validity, i.e. the observed variables converged to measure their unobserved variable OE.

Behavioral Intention

Six out of 8 items were retained to measure BI. The unobserved variable was not significantly different from the hypothesized. This was because only 3 observed variables were dropped.
The first set of results suggested that the model was not fit. Results obtained including χ^2=13.797 and χ^2/DF=3.449 at P=.008, and RMSEA=.083 did not meet the required thresholds for good model fit (Hoe, 2008; MacLean & Gray, 1998; Kline, 1998). However, the remaining measurement indices indicated that the model was fit. For instance, GFI=.988, AGFI=.936, NFI=.995, RFI=.980, IFI=.996, TLI=.986, and CFI=.996 were all above the threshold of 0.9. Given that the study sample was way above the recommended sample of 200 for SEM, this model can be accepted on the basis that a chi-square is sensitive to sample size (Kline, 1998).

The AVE for this variable was 0.698, which was above the required 0.5 and also that all observed variables had significant relationships with the unobserved variable at P<0.001. This implied that there was convergent validity, i.e. the observed variables converged to measure their unobserved variable Behavioral.

Mental health

MH variable had 4 hypothesized constructs namely; 1) Skills with 4 items, 2) Practice with 5 measurement items, 3) Observational learning, with 8 measurement items, and 4) Moral degeneration which had 8 measurement items. Out of the 4 constructs, 3 were retained, including 1) Practice with 2 observed variables, 2) Practice with 2 observed variables and 3) Observational learning with 2 observed variables. Through a systematic elimination method, observed variables with low standardized estimates were deleted from the model. The unobserved variable MH in this model was significantly different from the hypothesized variable. This was because Skills as a construct was dropped from the model, In addition, 3 observed variables were removed from Practice, 6 observed variables were deleted from Observational learning, and 6 observed variables were deleted from Moral degeneration.
Results further revealed that the model was not fit based on the Chi-square obtained and a P-value of 0 (χ^2=39.061, DF=6, P=.000, χ^2/DF=6.510) (Hoe, 2008; MacLean & Gray, 1998; Kline, 1998). The obtained RMSEA of .124 was also above o.8. However, most of the measurement indices indicated that the mode was fit. For instance, GFI=.964, AGFI=.872, NFI=.975, RFI=.936, IFI=.978, TLI=.946, and CFI=.978 were all above or equal to the threshold of 0.9.

Further, we observed that the AVE for this variable was 0.782, which was above the required 0.5. This implied that there was convergent validity, i.e. the measurement items for each construct converged to measure their respective constructs. This was supported by the fact that each retained observed variable had a significant relationship with its parent construct as all P-values were below 0.001.

The obtained squared correlation of the two constructs (R^2) was 0.49, which was below the obtained AVE of 0.782, implying that there was discriminant validity between the three constructs of Skills, Practice and Observational learning. Each of these three was unique and its measurement items measured only that construct.

Based on the above findings, it was concluded that Skills, Practice and Observational learning measured MH.

5.2 Structural Equation Models for social media and mental health

The first test was conducted on the hypothesized model and it was found that the hypothesized model was not fitting the data well, having obtained a χ^2 of 724.240, χ^2 /DF of 42.602, GFI of .820, AGFI of .523, NFI of .431, RFI of -.205, IFI of .437, TLI of -.211, CFI of .428 and RMSEA of .341 were all bad model fit indices. Consequently, AMOS rules were followed in building a new structural model that explains SM and MH. This was done by eliminating weak and insignificant relationships. Hence a good number of the relationships were dropped. Figure 2 presents the final structural equation model for SM and MH of SM users.

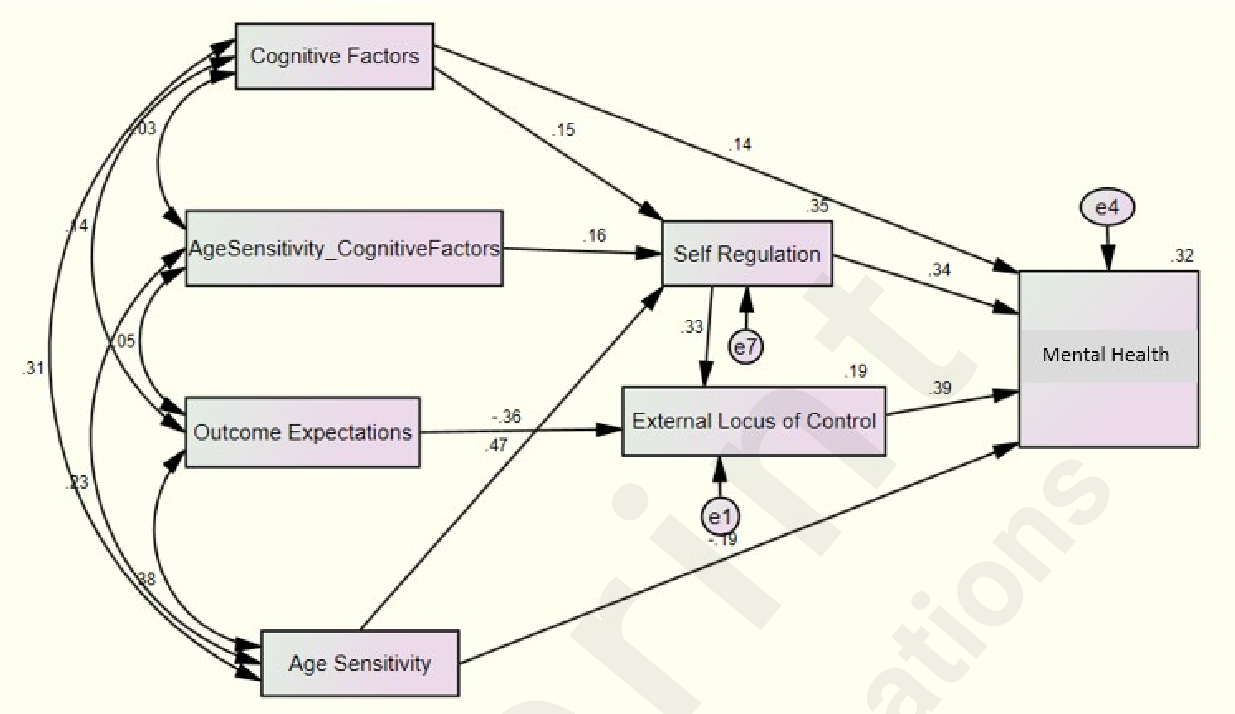

Figure 1: Model for social media and mental health

Latent variables; ILC BI were dropped since they did not fit the model. This led to elimination of the relationship between CF and ILC, ILC, and BI, BI and MH, and their mediation effects from the model.

The relationships that were retained are those between CF and MH; CF and SR; SR and MH; ELC and MH; SR and ELC; AS and MH; AS and SR; and OE and ELC. Table 1 presents the statistics for the structure model explaining SM and MH.

Table 1: SM and MH Model Fit Summary

X^2	**DF**	**P**	**X^2/DF**	**GFI**	**AGFI**	**NFI**	**RFI**	**IFI**	**TLI**	**CFI**	**RMSEA**
8.653	6	.194	1.442	.993	.968	.983	.940	.995	.981	.994	.035
						Estimate	**S.E.**	**C.R.**	**Beta**	**P**	**Hypothesis**
ELC		<---	OE			-.230	.031	-7.511	-.363	***	rejected
MH		<---	ELC			.411	.049	8.336	.385	***	H1b –accepted
MH		<---	CF			.209	.072	2.905	.135	.004	H2a –accepted
SR		<---	CF			.185	.055	3.332	.151	***	H3b –accepted
ELC		<---	SR			.390	.057	6.834	.330	***	H3c –accepted
MH		<---	SR			.425	.071	5.961	.337	***	H3d –accepted
MH		<---	AS			-.186	.053	-3.525	-.193	***	H3e –rejected
SR		<---	CF			.185	.055	3.332	.151	***	H4 –accepted
SR		<---	AS			.360	.035	10.174	.473	***	
SR		<---	AS * CF			.105	.030	3.561	.157	***	

Table 2: Squared Multiple Correlations for the proposed model

	Estimate
SR	.349
ELC	.190
MH	.319

Results in Table 1 reveal that the model was fit. For example, the obtained χ^2 =8.653 is below 20, χ^2 /DF=1.442 is below 3, P=.194 is above the recommended minimum of 0.5. The GFI=.993, AGFI=.968, NFI=.983, RFI=.940, IFI=.995, TLI=.981, and CFI=.994 were all above the threshold of 0.9 (Hoe, 2008). The obtained RMSEA of .035 was also far below the recommended maximum threshold of 0.08 for a model to be fit. Based on these indices, we conclude that the proposed model explains SM and MH of SM users.

The squared correlations seen in Table 2 reveal that CF, AS * CF and AS predicted 35% of SR (Beta=.349). Outcome expectation explained 19% of the changes in ELC (Beta=.190). On the other hand, CF, AS * CF, AS, SR and ELC predicted 32% of variance in MH (Beta=.319).

The proposed model is made up of six variables including 1) CF, 2) OE, 3) AS, 4) SR, 5) ELC and 6) MH. The first 3 variables i.e. CF, OE and AS are independent variables - though AS also doubles as a moderator variable. SR and ELC are mediators while MH is the dependent variable.

For enhanced mental health by SM users, increase OE, increase ELC, increase CF, increase SR, and reduce AS.

6. Theoretical implications

Generally, the current study provides empirical evidence in examining the cognitive and social learning theories on Mental health change. The three theories were triangulated and tested to see how best they explained the mental health of social media users. This was probably the first study that investigated SM and Mental health change in the region. As had been indicated in chapter one, most studies on e-health concentrated mainly technology transfer, adoption and sustainability. Little or nothing had been done on investigating the Mental health implications caused by adoption and usage of technology especially SM.

Specifically, this study makes a contribution to the body of knowledge on SM and MH by proposing a model for SM and MH. The proposed model was tested on empirical data and found to adequately explain how and why individuals learned new MH via SM.

Triangulation of the SLT [11] together with SCT by [13] and the SLT by [10] helped to solve the theoretical gap that existed in explaining behavioral change via SM. For instance, whereas [11] ably explained observational learning through role modeling, this theory falls short in explaining the CF, OE and SR influence on mental health as seen in [13]. Further, both [11] and [13] did not explain the influence of ELC that was found to influence behavior [13]. Yet still none of the three theories explained the role that age played in the learning process as had been argued by [56; 57], and [55].
The proposed model converges all the above constructs in trying to show how new MH and learned via SM platforms. Specifically, it espouses the influence that people's knowledge and beliefs have on their MH and how they control they control themselves while interacting via SM. Further, the model shows how individuals' OE motivate them to seek help form online communities, thereby learning new MH. The model also explains how an individual's level of AS influences the way they control themselves while learning from people of different age

groups via SM online communities.

7. Methodological implications

Prior research on SM and also that on behavioral change in general contexts used both qualitative and quantitative research methods. However, none used the SEM technique. Most of these studies used descriptive statistics, correlations and regression analysis as seen in chapter four. The qualitative methods applied were interviews and content analysis leading to development of frameworks formulated on the basis of untested and unverifiable hypotheses. Whereas these approaches helped highlight some of the challenges faced by e-health generally, it was difficult to establish the magnitude of the problems, given that measurement indices were uncertain. As seen in this study, descriptive statistics, correlation and regression analysis alone leaves a lot to be desired. While it shows the relationships exist, these relationships are treated in isolation. Moreover, in the end, they all have to work together towards achieving the main goal.

In this study, using SEM techniques, we were able to first of all, test and confirm the factors that measured constructs in the proposed model. The confirmed constructs were then modeled as a whole. Those that exhibited bad fit indices were eliminated until acceptable goodness of fit indices were obtained. Further, as seen in chapter four, all model hypotheses were tested and the magnitude of each hypothesis' influence is known and can be verified. The structural model gives clear mapping of the interaction between all model variables. Further, through bootstrapping, we were able to establish the significance of each mediation effect in the model.

Given the above therefore, we hope that, having gone through rigorous research methods, including data analysis using different approaches, testing of hypotheses through both data analysis as well as modeling techniques, we argue that the proposed model and all its findings is reliable and can be used to understand how new MH are learned via SM. It is in this spirit that we embolden adoption of SEM techniques in understanding SM and MH better.

References

1. Dewing M. (2012) SM: An introduction, *Library of parliament, Ottawa, Canada*, Publication No. 2010-03-E
2. Saleh J., Robinson B., Kugler N., Illingworth K., Patel P., and Saleh K. (2012). Effect of Social Media in Health Care and Orthopedic Surgery, *The cutting edge,* Volume 35 • Number 4, pg 294
3. Boyd B. M., and Ellison N. B. (2016) SM sites: definition, History and scholarship, *Journal of mediated computer communications*. Retrieve on 25th March 2016 from http://www.danah.org/papers/JCMCIntro.pdf
4. Leonardi P. M. and Huysman M. (2013) Enterprise SM: Definition, History, and Prospects for the Study of Social Technologies in Organizations, *Journal of mediated computer communications*, Vol. 19 (2013)
5. Protalinki E. (2015) Facebook passes 1.44B monthly active users and 1.25B mobile users; 65% are now daily users, VenterBeat. Retrieved on 26th March from: http://venturebeat.com/2015/04/22/facebook-passes-1-44b-monthly-active-users-1-25b-mobile-users-and-936-million-daily-users/
6. Statistica (2014a) Share of mobile internet users in selected countries who are active

WhatsApp users as of 4th quarter 2014, *Statistica*, Retrieved on 26th March, 2016 from: http://www.statista.com/statistics/291540/mobile-internet-user-whatsapp/
7. Statistica (2016b) Number of monthly active WhatsApp users worldwide from April 2013 to February 2016 (in millions), *Statistica*, Retrieved on 26th March, 2016 from: http://www.statista.com/statistics/260819/number-of-monthly-active-whatsapp-users/
8. Statistic Brain (2016) Skype Company Statistics, Statistic Brain. Retrieved on 26th March, 2016 from: http://www.statisticbrain.com/skype-statistics/
9. Bandura, A. (2000) Health promotion, *New York: Norton.*
10. Rotter, J. B. (1993). Expectancies. In C. E. Walker (Ed.), The history of clinical psychology in autobiography (vol. II) (pp. 273-284). *Pacific Grove,* CA: Brooks/Cole
11. Bandura, A. (1986). Social foundations of thought and action: A SCT. Englewood Cliffs, NJ: Prentice-Hall.
12. Hartley W. K., Tatum K, Gatto P., eds (2013). Raising the alarm: Patients, Providers & the Social Network making sense of meaningful use, *Health Journal of Little Rock*
13. Purdy H. C. (2011) Using the Internet and SM to promote condom use in Turkey, *Reproductive Health Matters*, Vol. 19(37):157–165
14. Levine D. (2009) Using New Media to Promote Adolescent Sexual Health: Examples from the Field, *Act Youth Center of Excellence*
15. Liang Y., Zheng X., Zeng D. D., Zhou X., Leischow S. J., and Chung W., (2015) Exploring How the Tobacco Industry Presents and Promotes Itself in SM, *Journal of medical internet research*, Vol. 17(1): e24
16. Mcquiston T. (2013) The Ultimate Guide To Craft Beer SM Marketing, *PorTable Bar Company*. Retrieved On 26th March, 2016 From: Https://TheporTablebarcompany.Com/Craft-Beer-Social-Media-Marketing/
17. Lozoff T. (2016) 4 Beer Companies With SM On Tap, *Mashable.* Retrieved On 26th March, 2016 From: Http://Mashable.Com/2010/08/27/Beer-Social-Media/
18. Rocha L. E. C , Liljeros F. and Holme P. (2016) Information Dynamics Shape The Sexual NetWorks Of Interne T-Mediated Prostitution, Sungkyunkwan University, Retrieved on 25th March 2016 from: http://arxiv.org/ftp/arxiv/papers/1003/1003.3089.pdf
19. Holme P. (2014) The Social, Economic and Sexual Networks of Prostitution, *ACM*, 978-1-4503-2745-9/14/04
20. FOTTRELL Q. (2013) Friends, prostitutes commingle on social networks, *MarketWatch*. Retrieved on 26th March, 2016 from: http://www.marketwatch.com/story/friends-prostitutes-comingle-on-social-networks-2013-05-16
21. Weiss R. (2010) Smart Phones, Social Networking, Sexting and Problematic Sexual Behaviors—A Call for Research, *Sexual Addiction & Compulsivity*, 17:241–246
22. Ware. C. M., and Goodmanson D. (2009) The Church & Social Networking: Industry Study, *Church Tech Review.* Retrieved on 26th march 2016 from: http://www.churchtechreview.com/wp-content/uploads/2009/04/churchesandsocialmedia.pdf
23. Boyd D. M., and Michigan N. B. E. (2007) Social Network Sites: Definition, History, and Scholarship, *State University*. Retrieved on 26th march 2016 from: http://mimosa.pntic.mec.es/mvera1/textos/redessociales.pdf
24. Smith K, Christakis N. (2008) Social networks and health. *Annu Rev Sociol*, 34:405–429.
25. Chou W. Y., Hunt, Y. M., Beckjord, E. B., Moser, R. P., and Hesse, B.W. (2009) SM use in the United States: implications for health communication, *J Med Internet Res*.11:e48.

26. Centola, D. (2013) SM and the Science of MH, *American Heart Association*
27. Centola D (2010) The spread of behavior in an online social network experiment, *Science*. 329: 1194–1197.
28. Adewuyi E. O. and Adefemi, K. (2016) Behavior Change Communication Using SM: A Review, *The International Journal of Communication and Health*, 2016 / No. 9
29. Korda, H., and Itani, Z. (2011) Harnessing SM for Health Promotion and Behavior Change, *Health Promotion Practice*, Sage Journals, Vol 14, Issue 1, 2013
30. Kituyi G. M., Isabalija R., and Mbarika V. (2013). A Framework for Sustainable Implementation of E-Medicine in Transitioning Countries, *International Journal of Telemedicine and Applications,* Volume 2013, Article ID 615617, 12 pages
31. Isabalija S., Kituyi G. M., Rwashana A.S., and Mbarika V. (2011). Factors affecting the adoption, implementation and sustainability of telemedicine information systems in Uganda. *Journal of Health Informatics in Developing Countries*, Vol. 5, No 2 (2011)
32. Jin L., Chen S. D. Y., Wang T., Hui P., and Vasilakos A. V. (2013) Understanding User Behavior in Online Social Networks: A Survey, *IEEE Communications Magazine*
33. Benevenuto F., Rodrigues T., Cha M., and Almeida V. (2016) Characterizing User Behavior in Online Social Networks, *University of Wisconnsin-Madison;* Retrieved on 25th March 2016 from: http://pages.cs.wisc.edu/~akella/CS740/S12/740-Papers/BEN+09.pdf
34. Han Y., and Tang J. (2015) Probabilistic Community and Role Model for Social Networks, *ACM.*
35. Das S., Lavoie A. (2014) The Effects of Feedback on Human Behavior in SM: An Inverse Reinforcement Learning Model, in: Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France, *International Foundation for Autonomous Agents and Multiagent Systems*
36. Ioanăs E., Stoica I. (2014) SM and its Impact on Consumers Behavior, *International Journal of Economic Practices and Theories,* Vol. 4, No. 2,
37. BBC (2008) Social Networking A quantitative and qualitative research report into attitudes, behaviors and use, *BBC Office of communications*
38. Bandura A. (2001) SCT of Mass Communication, *Mediapsychology*, *3*, 265–299
39. Bachar K. J. (2016) An Overview of SLT (SLT), *College of Public Health, University of Arizona*
40. Bandura, A. (1990). Mechanisms of moral disengagement. In W. Reich (Ed.), Origins of terrorism: Psychologies, ideologies, theologies, states of mind (pp. 161-191). *Cambridge: Cambridge University Press*.
41. Bandura, A. (1982). The psychology of chance encounters and life paths. *American Psychologist, 37*, 747–755.
42. Bayrón, C.E (2013) SCT, Entrepreneurial Self-Efficacy and Entrepreneurial Intentions: Tools to Maximize the Effectiveness of Formal Entrepreneurship Education and Address the Decline in Entrepreneurial Activity, *Revista Griot*. Vol. 6, 1, Pg 66-77
43. WHO (2000) Health and Health Behaviour among Young People, *World Health Organization*
44. NIHCE (2007) Behaviour change at population, community and individual levels, *National Institute for Health and Clinical Excellence*
45. Orji R. (2014) Exploring the Persuasiveness of Behavior Change Support Strategies and

Possible Gender Differences, *University of Saskatchewan*

46. Sebstad J., and Manfre C. (2011) Behavior Change Perspectives on Gender and Value Chain Development, *United States Agency for International Development*, FIELD Report No. xx:
47. Flandorfer P., Wegner C., and Buber I. (2010) Gender Roles and Smoking Behaviour; Working paper, *Vienna Institute of Democracy*
48. Lawson T. (2014) A Conception of Ontology, *Cambridge*
49. Guarino N., Oberle D., and Staab S. (2009) What Is an Ontology? Handbook on Ontologies, International Handbooks on Information Systems, *Springer-Verlag Berlin Heidelberg*, DOI 10.1007/978-3-540-92673-3
50. Suhr, D. D. (2017) Exploratory or Confirmatory Factor Analysis? *Sas*, Retrieved on March 20th 2017 from http://www2.sas.com/proceedings/sugi31/200-31.pdf
51. Hoe S. L. (2008) Issues and Procedures in adopting SEM Technique, Quantitative methods inquiry, *Journal of applied quantitative methods*
52. MacLean, S. and Gray, K. (1998) SEM in market research, *Journal of the Australian market research society*
53. Chin, W. W (1998) Issues and opinion on SEM, *MS Quarterly*, 22, 1 pp. 7-16
54. Joreskog K. G and Sorbom D (1993) LISREL6 – Computer program, *Moorseville, IN, Scientific Software*
55. Hoelter D. R (1983) The analysis of convariance structures: goodness-of-fit indices, *Socialogical methods and research* 11, pp. 325-344
56. Garver M. S. and Mentzer, J. T. (1999) Logistics research methods: employing structural equation modeling to test for validity, *Journal of Business Logistics*, 20, 1 pp. 33-57
57. Steiger, J. H. (1990) Structural model evaluation and modification: an interval estimation approach, *Multivariate behavioral research*, 25 pp. 173-180
58. Kline, R. B. (1998) Principles and practice of SEM, *New York, Guilford Press*
59. Venkatesh V., Morris, M. G., Davis, G. B., and Davis. D. (2003) User Acceptance of Information Technology: Toward a Unified View, *MIS Quarterly.* Vol. 27, No. 3, pp. 425-478
60. Anderson, A. (2005). An introduction to theory of change. Evaluation Exchange, Summer,VolumeXI, 2. http://www.hfrp.org/evaluation/the-evaluation-exchange/issue-archive/evaluation-methodology/an-introduction-to-theory-of-change.
61. Blalock S. J., Bone L., Brewer N. T., Butterfoss F. D., Champion V. L., Epstein R. E (2016) MH and Health education: Theory, Research and Practice. Karen G., Rimer B. K., Viswanath K. (Ed.), Perelman School of Medicine, University of Pennsylvania, Retrieved on March 3rd 2016 from: http://www.med.upenn.edu/MHhe4
62. Bulsara C. (2016) Using a Mixed Methods Approach to Enhance and Validate Your Research, The University of Notre Dame. Retrieved on 27th march 2016 from: https://www.nd.edu.au/downloads/research/ihrr/using_mixed_methods_approach_to_enhance_and_validate_your_research.pdf
63. De Lisle J. (2016) The Benefits And Challenges Of Mixing Methods And Methodologies: Lessons Learnt From Implementing Qualitatively Led Mixed Methods Research Designs in Trinidad and Tobago, *Caribbean Curriculum* Vol. 18, 2011, 87–120.
64. Lindova J., Novotna M., Havlı´cˇek J., Jozı´fkova E., Skallova A., Kolbekova P., Hodny Z., Livingston G., Minushkin S., Cohn D (2014). Hispanics and Health Care in the United States: Access, Information and Knowledge, *Robert Wood Johnson Foundation*

65. Sedgwick, P. (2014) Cross sectional studies: advantages and disadvantages, *BMJ*; 348: g2276
66. Wandersman Abraham (2009) Four Keys to Success (Theory, Implementation, Evaluation, and Resource/System Support): High Hopes and Challenges in Participation. *Springer Science Business Media*, LLC 2009 *Policy* Series: Health policy for children and adolescents Issue 1; International Report