Impact of addiction of online platforms on quality of life: Age and Gender as moderators

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Abstract

The excessive usage of online platforms is inviting several unwanted problems in the society. The excessive use of online platforms is adversely interfering in many social activities. This uncontrolled and excessive use of online platforms is causing addiction to the users. This is unexpectedly impeding the normal social flow of life culminating an adverse effect on the individuals' quality of life. Studies reveal that age and gender have influence towards addiction. In this background, the purpose of this study is to identify the factors impacting addiction of online platforms. From studies of several addiction theories, some hypotheses have been formulated and a conceptual model has been developed. These have been validated by Partial Least Square – Structural Equation Modeling (PLS-SEM) analysis with the help of survey involving 320 usable respondents. The study highlights that loneliness, perceived enjoyment, depression, perceived ease of use and perceived usefulness act as vital predictors of addiction of online platforms that impacts quality of life. The moderating factors age and gender are found to have effective impacts on the influence of predictors on the addiction of online platforms. The article is ended mentioning the limitations of this study incorporating the scopes for the future researchers to nurture the untouched points.

Keywords: Addiction, Age, Gender, Online platforms, Quality of life

1   Introduction

Studies reveal that more than 32% world population use online platforms for various transactions (E marketer, 2016). Various banking and shopping activities can be completed by e-commerce sites. Even, social networking sites can help to understand the consumers' behaviour (Lee et al., 2014; Chatterjee et al., 2020b). The household consumers are expected to use different kinds of online platforms for shopping of grocery items as they become more tech-savvy (Sarin et al., 2020; Grover & Kar, 2020). Thus, use of different online platforms is providing many advantages to the users (Whiteside et al., 2018). This would develop the habit of the users to use online platforms more that might indulge the individuals to eventually become victims of addiction in using online platforms (Augner & Hacker, 2012; Choliz, 2012). This addiction is apprehended to affect quality of life (Choi & Seo, 2015; Mard & Cui, 2017; Soral et al., 2020). Several studies highlighted that age and gender of individuals might affect the extent of addiction of individuals (Hu et al., 2019). The addiction habit affects the individuals' social activities (Boreham, 2016; Arpaci et al., 2018). Addiction of online platforms includes addiction of social media, smartphones, online shopping, online banking and so on (Disen & Deshpande, 2018; Wang, 2019). Excessive use of different online platforms causes online addiction. It has negative impacts towards several areas of human life affecting the

quality of life (Park & Lee, 2012; Xue et al., 2018). Use of online platforms initially invites pleasure, interest, and excitement to the users. However, this motivation induces the users to use the system frequently causing addiction. This causes harm to the society affecting the users' quality of life (Jiang, 2014; Carlson et al., 2015; Ram & Zhang, 2018). Easiness of use of a technology helps a user to frequently use that technology (Dolan et al., 2016; Carlson et al., 2017; Grover et al., 2018, 2019). Stress causes depression and the depressed persons keep themselves engaged in frequently using a technology to be relieved from the depression. This has been seen in other studies in smartphone usage where the users were addicted (Kumar et al., 2020). Some people exhibit avoidant attitude, and this feeling is associated with the sense of loneliness (Wei et al., 2005; Lee et al., 2019). Feelings of usefulness of a system lead an individual to use the system frequently. This causes addiction to that technology (Mc Kinley et al., 2016; Wang et al., 2018). The perceived enjoyment is considered as an important predictor of use-behaviour of a system as is found from the other studies (Van der Heijden, 2003; 2004; Baccarella et al., 2018). It has been already stated that age and gender of individuals are perceived to impact addiction to any technology. But, how, to what extent and in which way, these two factors influence addiction of online platform have remained under studied.

In this background the objectives of this studies are as follows.

1. To identify the factors impacting addiction of online platforms by the users.

2. To examine the moderating effects of age and gender for the addiction of online platform.

3. To understand how the addiction of online platforms impacts quality of life of the users.

The rest of the article is structured as follows. Discussions have been made on the theoretical backgrounds. Thereafter, hypothesis have been formulated and a conceptual model has been developed. Next, hypotheses have been tested statistically and the results have been discussed. Then discussions have been made on theoretical contributions and practical implications followed by mentioning of limitations of this study with future scope of research.

2 Theoretical Background and Development of Conceptual Model

2.1 Theoretical Background

Addiction is considered as a special behavioural manifestation of an individual. This manifestation leads the individual to have lost control that causes harmful consequences (Shelton et al., 2014). This is considered as a psychiatric motivational disorder (Collier, 1993). To identify antecedents of addiction, some relevant theories are considered convenient. The challenges and objectives of different addiction theories are many folds. It is important to identify how addiction occurs in the society and what are its remedies (Kim et al., 2017). Studies reveal that all the theories do not match to exhaustively interpret addiction to any technological use. But the Adult Attachment Theory (Fraley & Shaver, 2000) provides that addiction in any technology is impacted by the human centric traits like loneliness and depression (Kim et al., 2017; Csibi et al., 2019). From the study of Adult Attachment Theory, it is evident that younger individuals use online platforms as an attachment object to be relieved from depression and loneliness (Jeon & Jang, 2014; Fox & Moreland, 2015). From the study of the Tension Reduction Theory (Cappell & Greelay, 1987), it is transpired that depression can supplement an individual for impairing control that would lead to inimical consequences

(Collier, 1993). The Tension Reduction Theory subscribes that addiction to any specific technological use emerges from the feelings of loneliness and depression (Hassanbeigi et al., 2013; Lee et al., 2019). In this study, we have also lent the idea of Technology Acceptance Model (TAM) (Davis et al., 1989) wherefrom two core constructs, perceived usefulness and perceived ease of use have been used. This model is a parsimonious model and has been considered as a foundation of adoption in technology acceptance (Dolan et al., 2012). TAM finds its appropriate applications when a technology is adopted by a user for the first time (Yi et al., 2009). Besides, the two core exogenous constructs of TAM, perceived usefulness and perceived ease of use include other important beliefs (Park, 2009). It is further to mention here that TAM has been extended subsequently taking into account another factor perceived enjoyment while another study was conducted for investigation of the use of websites by the users (van der Heijden, 2003; Chung & Tan, 2004). With this conception, we have used these beliefs which are loneliness, depression, perceived enjoyment, perceived usefulness, and perceived ease of use as exogenous variables. In addition to these exogenous variables, addiction is also found to have been affected by age and gender of the users (Korpinen & Paakkonen, 2011; Borcham, 2016).

2.2 Development of hypotheses and conceptual model

From the conception of literature review, different theories, and models, we have identified the salient independent factors that impact addiction of online platforms. Now, we will discuss each of the constructs and would take an attempt to formulate some Hypotheses that would help us to develop the conceptual model.

2.2.1 Loneliness (LON)

Humans possess a special behavioural characteristic by which humans exhibit an avoidant-attachment style. It is perceived to have been closely associated with the feelings of loneliness to impede inter-personal relationship (Yi et al., 2012; Chatterjee, 2020a). The feelings of being alone or being separated from others bring in the sense of loneliness (Tomaka et al., 2006). These individuals like to live alone and even when they are in a community, they feel that they are still alone. Use of modern technologies by the individuals helps them to be relieved from the strain of loneliness (Wei et al., 2005; Jeong et al., 2016). This idea of getting relief from the feelings of loneliness through frequent use of a particular technology leads the individuals to eventually be addicted to that technology (Yang & Lin, 2014; Kim & Kim, 2016; Chatterjee et al., 2019). This concept has also been supported already in other studies (Park & Lee, 2012). All these inputs lead to formulate the below-mentioned hypothesis.

H1: Loneliness (LON) of the individuals has a significant impact towards the Addiction of Online Platforms (AOP).

2.2.2 Perceived Enjoyment (PEN)

Studies of online games helped to infer that hedonic values are related with the concept of enjoyment and it influences user behaviour (Yang & Lin, 2014). Perceived enjoyment is interpreted as the degree to which the concerned activity surrounding the use of a technology is "perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated" (van der Hijden, 2003). We have evidence that perceived enjoyment acts as an effective predictor to ascertain usage behaviour of humans which has been observed in studies conducted to analyse use-behaviour of individuals using Social Networking Services (SNSs) (Han & Windsor, 2011). The study helps us to conceptualize that individuals' feelings

of enjoyment or playfulness emerge from the interactions of the users with the environment-related factors (Lee & Tsai, 2010). The feelings of enjoyment emerge from the use of a technology like playing of online games or videos or use of Social Media and so on which are not related with task-oriented issues (Shin, 2010; Wei & Lu, 2014). People use online platforms for intrinsic as well as extrinsic reasons. Intrinsic motivation is related with entertainment and pleasure issues and users of different ages are found to use online platforms even by playing games and so on. This tendency of having entertainment, enjoyment, playfulness and pleasure propels the users to use frequent and uncontrolled use of online platforms instrumental for addiction (Lee & TSI, 2010; Sarin et al., 2020; Grover & Kar, 2020). These discussions lead to propose the following Hypothesis.

H2: Perceived Enjoyment (PEN) of the users has a significant impact on Addiction of Online Platforms (AOP).

2.2.3 Depression (DEP)

Depression of individuals would bring in addiction under various contexts (Yeo et al., 2014; Gong et al., 2020). It appears from the different studies that individuals are found to be aligned for being involved using various types of online platforms. This will provide the individuals to be relieved from depression (Kim et al., 2007; Wang et al., 2019). Study was conducted on the Korean students about depression. It revealed that if the students suffer from any sort of depression, they are inclined to use different online platforms. This will help them to be relieved from that depression (Jeon & Jang, 2014). Depression is considered as a special mental status of individuals (Yeo et al., 2014; Chen et al., 2017; Lee et al., 2019). The individuals perceive that if they frequently use social media, smartphone, and other online platforms, they might get relief from depression. It leads them to be addicted to that technology (Kim & Kim, 2016). Thus, this mental state of humans finds its solution to remove this strain-oriented trait through the frequent use of any technology (Yi et al., 2012). This will help the humans to come out from depression. This frequent use of the technology induces the users to be addicted to that technology (Kim et al., 2007). These inputs help us to formulate the following hypothesis.

H3: Depression (DEP) of individuals has a significant impact on Addiction of Online Platform (AOP).

2.2.4 Perceived Ease of Use (PEU) and Perceived Usefulness (PU)

In consonance with the concept of Technology acceptance Model (Davis et al., 1989), perceived usefulness is defined as "the degree to which an individual believes that using the services will contribute to reaching a particular objective". It is believed that increased usefulness of a system is associated with the use of the system frequently inviting addiction to it (Taylor & Todd, 1995). Thus, whenever the users perceive that by using online platforms, they will be able to successfully perform their jobs, they will start using the online platform frequently that would lead to addiction to that (Bisen & Deshpande, 2018; Chatterjee et al., 2019). Conception of usefulness of a system induces an individual to use that system frequently. It leads to addiction as has been observed in the study of internet addiction (Sulaiman et al., 2019). Hence, it can be inferred that perceived usefulness might act as an effective predictor of addiction of online platforms. If an individual feels easy and fruitful to use a system, the individual exhibits the tendency to use that system (Lee et al., 2007; Mard & Cui, 2017). This sense and perception of easiness to use a system impacts one's cognition and it also influences one's behaviour and the individual does not hesitate to frequently use the system resulting in addiction to that system (Kwon et al., 2013). Ease of use of a system may be considered an influential predictor for addiction (Jiang, 2014). In another study, it has appeared that ease of use has impacted an

individual in addiction to internet (Arpaci et al., 2018). Hence, it can safely be inferred that ease of use may be one of the reasons for addiction with a system. With all these inputs, the following hypotheses are formulated.

H4: Perceived Ease of Use (PEU) has a significant impact on Addiction of Online Platforms (AOP).

H5: Perceived Usefulness (PU) has a significant impact on Addiction of Online Platforms (AOP).

2.2.5 Addiction of Online Platforms (AOP) and Quality of Life (QL)

Addiction to any technology use is construed as an unhealthy behaviour of the individuals. It has been observed that smartphone addiction impacts adversely on the health of the users (Hong et al., 2012). Here, smartphone acts as a medium to online platform. Such type of use of online platforms in an uncontrolled way severely affects the individuals. Even, the professionals' daily works are likely to be hampered if they are always engaged to use online platforms for other purposes (Park & Lee, 2012; He et al., 2019). This has an adverse effect on the quality of life of the professionals also. Frequent usage of the online platforms keeps the users always engaged in the online activities. The users cannot control them to be dissuaded from being engaged in using the online platforms. This will lead to deterioration of the quality of life of the users (Costanza et al., 2008; Whiteside et al., 2018). Here quality of life is associated with personal life and professional life of the users. Thus, addiction of online platforms by the users negatively affects their quality of life. These inputs help us to develop the following Hypothesis.

H6: Addiction of Online Platforms (AOP) negatively affects the Quality of Life (QL).

2.2.6 Age and Gender as moderators

In this study, we have been able to hypothesize five hypotheses affecting addiction of online platforms covering H1, H2, H3, H4, and H5. Studies reveal that age factor has a dominating effect to impact on these five linkages affecting addiction of online platforms (Cameron, 1969). It has been observed in different studies that age factor of individuals is instrumental to control the individual-centric traits and technological issues that impact the addiction of online platforms (Nysveen et al., 2005; Jeon & Jang, 2014). In the study of Cameron (1969), the effect of age has been divided in different age group marking as young-adult having age of 18-35 years, mid-aged adult having age of 36-55 years and older adult having age more than 55 years. In our study, we have categorized the users of online platforms into two categories, young-adult (18-35 years) and mid-aged adult (36-55 years) as number of online users in these two categories are relatively high (Csibi et al., 2019; Sulaiman et al., 2019). Details will be discussed, how individuals of these two categories of age-group affect the different linkages covering hypotheses H1 to H5. These discussions propose to formulate the following hypotheses.

H7: Age of individuals impacts on the Loneliness-Addiction of Online Platforms linkage covering H1.

H8: Age of individuals impacts on the Perceived Enjoyment-Addiction of Online Platforms linkage covering H2.

H9: Age of individuals impacts on the Depression-Addiction of Online Platforms linkage covering H3.

H10: Age of individuals impacts on the Ease of Use-Addiction of Online Platforms linkage covering H4.

H11: Age of individuals impacts on the Usefulness-Addiction of Online Platforms linkage covering H5.

Again, this study perceives that like age factor of individuals, the gender factor has also impact on the linkages between the different predictors of addiction with addiction of online platforms as is evident from other studies (Van Deursen et al., 2015; Yang et al., 2018). Another study has also revealed that human-centric traits like loneliness, perceived enjoyment, depression affect the women and men with varied extent under identical conditions (Ameen et al., 2018). Hence, the author has perceived that gender may also be considered as a moderator to moderate the linkages covering H1 to H5. This has led to hypothesize as follows:

H12: Gender acts as a moderator to impact the Loneliness-Addiction of Online Platforms linkage covering H1.

H13: Gender acts as a moderator to impact the Perceived Enjoyment-Addiction of Online Platforms linkage covering H2.

H14: Gender acts as a moderator to impact the Depression-Addiction of Online Platforms linkage covering H3.

H15: Gender acts as a moderator to impact the Ease of Use-Addiction of Online Platforms linkage covering H4.

H16: Gender acts as a moderator to impact the Usefulness-Addiction of Online Platforms linkage covering H5.

After formulation of these hypotheses, the conceptual model is developed and is shown in Figure1.
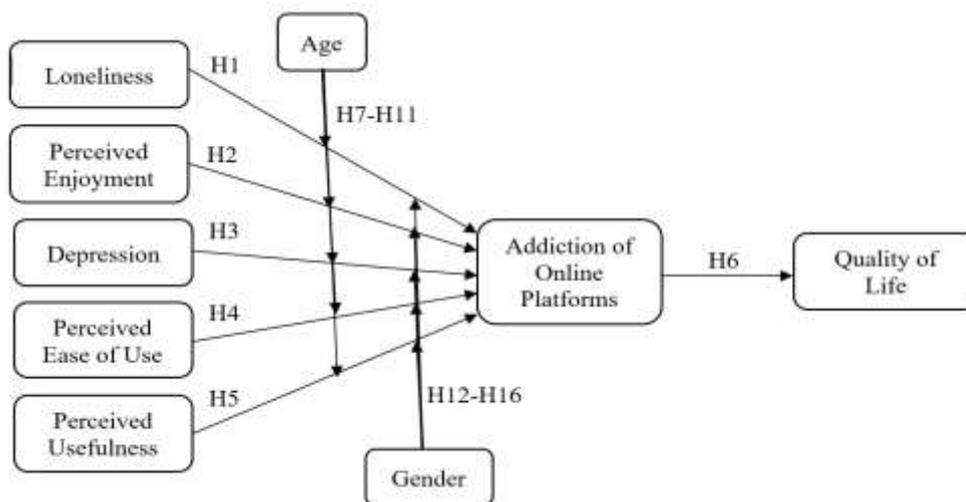
Figure 1: The Conceptual Model

3   Research Methodology

The hypotheses and the conceptual model are required to be statistically tested. The conceptual model shows that the number of independent variables is more than the number of dependent variables. Hence, it is cogent to apply Partial Least Square (PLS) – Structural Equation Modeling (SEM) technique (Abdi, 2010). The PLS-SEM approach involves survey to obtain feedbacks from the usable respondents against some structured set of questions (questionnaire) in the form of statements (measurement instruments).

3.1 Measurement Instruments

The concepts of the constructs have helped us to prepare the set of questions (Questionnaire) which could ensure content validity. The process of preparing the questionnaire was undertaken through some step-by-step correctional approaches. It includes thematic literature analysis, in depth interpretation of the constructs, qualitative studies, pre-test, opinion of some experts specialized in the domain of this study and pilot test (Carpenter, 2018). In this way, 33 questions in the form of statements were prepared. The details of the measurement instruments along with the sources are provided in a tabular form in Appendix 1.

3.2 Data collection strategy

To collect the names and email ids of the prospective online users, we attended some conferences held in different parts of India. In those conferences, discussions took place on the subject that covers the domain of this study. In these conferences, we could target some resource persons. They helped us by supplying lists of different potential online users with varied age, qualification and so on. Their supplied lists contained 906 potential respondents. We took their consent for providing us the feedbacks against those 33 questions. They were requested to provide their responses within three months (October 2019 to December 2019). We sent them two reminders in the meantime with a request to provide their responses in time. We received 391 responses within the stipulated period. The response rate is 43.1%. It was observed that out of 391 responses, 71 responses were incomplete. These were perceived not to yield any effective result through analysis. We did not consider those 71 responses. We started our statistical analysis with 320 usable responses against 33 questions. These are well within the permissible range (Deb & David, 2014). The demographic information of the respondents is shown in Table 1.

Particulars	Characteristics	Number	Percentage (%)
Gender	Male	224	70
	Female	96	30
Age	Young adult (18-35 years)	192	60
	Mid-aged adult (36-55 years)	128	40
Education	Undergraduate	48	15
	Graduate	70	22
	Postgraduate	144	45
	Researcher/PhD	58	18

Table 1: Demographic Information of the respondents

4   Data analysis and results

4.1   Data analysis for validity and reliability

For identifying the convergent validity of the 33 research instruments, Loading Factor (LF) of each item has been measured. For ascertaining reliability, consistency, validity of the constructs, we have estimated Average Variance Extracted (AVE), Cronbach's alpha (α) and Composite Reliability (CR) of each construct respectively (Fornell & Larcker, 1981). To examine multicollinearity defects, Variance Inflation Factor (VIF) of each construct has been estimated. On computation, it appears that all the parameters are within the acceptable range. This confirms that the instruments are reliable, and the constructs are reliable, consistent, and

valid. The constructs do not suffer from the defects of multicollinearity. The entire results of measurement property are shown in Table 2.

Moderator / Construct	Mean	SD	LF	t-value	AVE	Alpha (α)	CR	VIF	Number of items
Age	4.71	1.46	1.00		1.00		1.00		
Gender	3.81	1.87	1.00		1.00		1.00		
LON					.84	.88	.91	4.8	5
LON1	3.2	1.2	.85	26.41					
LON2	4.1	1.4	.99	25.27					
LON3	4.6	1.9	.97	39.11					
LON4	3.8	1.8	.88	27.01					
LON5	2.9	1.1	.85	19.48					
PEN					.86	.94	.96	3.7	5
PEN1	2.7	1.4	.84	21.21					
PEN2	2.9	1.3	.98	18.78					
PEN3	3.8	1.9	.90	12.11					
PEN4	3.9	1.9	.96	26.12					
PEN5	4.8	1.5	.95	29.52					
DEP					.81	.91	.98	3.3	5
DEP1	4.8	1.6	.87	27.48					
DEP2	4.8	1.6	.88	22.12					
DEP3	4.1	1.9	.90	18.99					
DEP4	3.1	1.1	.84	29.37					
DEP5	4.5	1.1	.99	21.00					
PEU					.84	.86	.97	4.9	5
PEU1	3.2	1.6	.90	26.81					
PEU2	3.5	1.4	.87	27.48					
PEU3	4.1	1.7	.88	29.01					
PEU4	3.8	1.7	.93	37.35					
PEU5	4.9	1.1	.99	26.81					
PU					.87	.90	.92	3.7	5
PU1	3.6	1.8	.88	28.21					
PU2	3.2	1.7	.89	19.34					
PU3	3.0	1.2	.99	23.11					
PU4	2.8	1.4	.95	26.42					
PU5	3.7	1.5	.84	29.03					
AOP					.82	.89	.93	3.9	4
AOP1	2.9	1.3	.95	26.41					
AOP2	4.9	1.4	.90	19.34					
AOP3	4.7	1.7	.88	28.95					
AOP4	3.1	1.9	.89	21.06					
QL					.84	.92	.94	4.9	4
QL1	3.7	1.8	.99	24.81					
QL2	4.8	1.8	.97	27.21					
QL3	3.9	1.6	.85	21.11					
QL4	4.4	1.4	.84	19.39					

Table 2: Measurement Properties

4.2 Discriminant validity test

It is always expected that each item should strongly interpret its own construct and would weakly explain the other constructs. To examine this, discriminant validity test is needed to

be conducted (Fornell & Larcker, 1981). For this, correlation coefficients for each construct with other constructs have been computed. It is found that they all are less than the corresponding square root of AVE of each construct. This confirms discriminant validity. The entire results are shown in Table 3.

Moderator/ Construct	Age	Gender	LON	PEN	DEP	PEU	PU	AOP	QL	AVE
Age	Single Item									1.00
Gender	.24	Single Item								1.00
LON	.32	.27**	.92							.84
PEN	.26*	.36	.27	.93						.86
DEP	-.29	.38	.29*	.28*	.90					.81
PEU	.34	-.22	.41**	.27*	.32	.92				.84
PU	.24	.32*	.43	.24*	.37*	.31	.93			.87
AOP	.32**	-.44	.36	-.36**	.41	.36*	-.33	.91		.82
QL	-.26	.41	-.21	.41	-.43	.47	.37*	.39	.92	.84

Table 3: Discriminant validity test

4.3 Path analysis using Structural Equation Modeling (SEM)

To ascertain how the latent variables are related, SEM is conducted. It also confirms if the model is in order or not. For this, Root Mean Square Error (RMSE), ratio of chi square and degree of freedom, Comparative Fit Index (CFI), Normed Fit Index (NFI), and Tucker–Lewis Index (TLI) have been measured. Their estimated values are 0.03, 2.041, 0.97, 0.99 and 0.98 respectively which all are within the permissible range as the RMSE has maximum value 0.07 (Steiger, 2007), chi square and degree of freedom ratio has the maximum value 3 (Kline, 2005), CFI has the minimum value 0.93 (Hair et al., 2006), NFI has the lowest permissible value 0.95 (Schumacker & Lomex, 2004) and TLI has the minimum value 0.95 (Sharma et al., 2005). Hence, the model after validation is in order. Through this, we have been able to find out the coefficient of determinants (R^2), p-values and path coefficients. The entire results are shown in Table 4.

Measure	R^2 values	Hypotheses	Path Coefficients	p-values	Remarks
Effect on AOP	0.52				
by LON		H1	0.32	*(p<0.05)	Supported
by PEN		H2	0.46	*(p<0.05)	Supported
by DEP		H3	0.39	**(p<0.01)	Supported
by PEU		H4	0.46	*(p<0.05)	Supported
by PU		H5	0.52	*(p<0.05)	Supported
Effect on QL	0.71				
by AOP		H6	-0.49	***(p<0.001)	Supported

Table 4: R^2 values, p-values, Path Coefficients and Remarks

The conceptual model after validation has been shown in Figure 2.
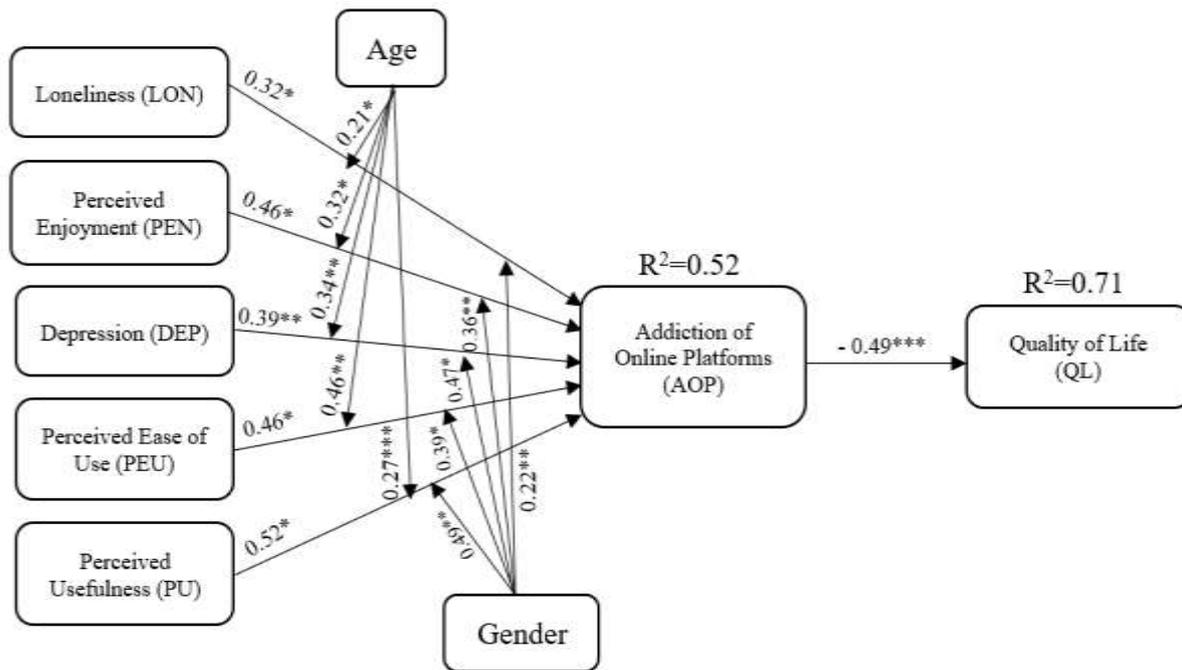
Figure 2: Validated model

By PLS-SEM analysis, we have found out the path weights of all the direct linkages. Also, we have been able to estimate the path weights of the two moderators affecting the five linkages covering H1, H2, H3, H4 and H5. The entire results are shown in Table 5.

Path	Path weight	p-value	Hypothesis	Remarks
LON→AOP	.32	*(p<0.05)	H1	Supported
PEN→AOP	.46	*(p<0.05)	H2	Supported
DEP→AOP	.39	**(p<0.01)	H3	Supported
PEU→AOP	.46	*(p<0.05)	H4	Supported
PU→AOP	.52	*(p<0.05)	H5	Supported
AOP→QL	-.49	***(p<0.001)	H6	Supported
(LON→AOP) × Age	.21	*(p<0.05)	H7	Supported
(PEN→AOP) × Age	.32	*(p<0.05)	H8	Supported
(DEP→AOP) × Age	.34	**(p<0.01)	H9	Supported
(PEU→AOP) × Age	.46	**(p<0.01)	H10	Supported
(PU→AOP) × Age	.27	***(p<0.001)	H11	Supported
(LON→AOP) × Gender	.22	**(p<0.01)	H16	Supported
(PEN→AOP) × Gender	.36	**(p<0.01)	H15	Supported
(DEP→AOP) × Gender	.47	*(p<0.05)	H14	Supported
(PEU→AOP) × Gender	.39	*(p<0.05)	H13	Supported
(PU→AOP) × Gender	.52	**(p<0.01)	H12	Supported

Table 5: Path weights with consideration of moderators

4.4 Moderator Analysis

To examine the moderating effects of the moderators (Age and Gender) on the five linkages covering H1, H2, H3, H4 and H5, a Multi Group Analysis (MGA) has been conducted. For this, help of Smart-PLS with the use of accelerated bias corelated bootstrapping with consideration of 6000 resamples has been taken for computing the path coefficient differences and p-value

differences relating to two selected categories for each moderator (for age, two categories are considered, young adults covering range of age as 18-35 years and mid-aged adults covering range of age 36-55 years, for gender obviously two categories are considered, male and female). The effects of the moderators are perceived to be significant if the difference of p-values for each moderator concerning to two categories as mentioned above, becomes either smaller than 0.05 or greater than 0.95 (Hair et al., 2016). The results highlight that both the moderators have significant effects on each of the five linkages that cover H1, H2, H3, H4 and H5. The results are shown in Table 6.

Path	Moderator	Diff. of path coefficients	Diff. of p-values	Remarks
LON →Age →AOP	Age	0.116	0.002	Significant
PEN → Age →AOP	Age	0.121	0.004	Significant
DEP → Age →AOP	Age	0.132	0.042	Significant
PEU → Age →AOP	Age	0.115	0.032	Significant
PU → Age →AOP	Age	0.124	0.014	Significant
LON → Gender →AOP	Gender	0.152	0.004	Significant
PEN → Gender →AOP	Gender	0.141	0.007	Significant
DEP → Gender →AOP	Gender	0.116	0.016	Significant
PEU → Gender →AOP	Gender	0.143	0.032	Significant
PU → Gender →AOP	Gender	0.139	0.024	Significant

Table 6: Multi Group Analysis (MGA) for testing moderator effects

4.5 Common Method Bias (CMB)

Since the study stands on the foundation of self-reported data, it is essential to see if these data are suffering from the defects of CMB. However, for reducing the possibility of occurrence of CMB, at the time of survey, the respondents were assured of confidentiality as well as anonymity. To alleviate this, a post-hoc Harman's single factor test has been conducted. On verification, it appears that the first factor emerged for 41.3% of the variance. It is less than the cut-off (highest) value 50% as recommended by Podsakoff et al. (2003). Thus, the results highlight that there is no CMB in this study. As such, there is no chance of distortion of the predicted results of this study.

4.6 Results for data analysis

Through studies of literature and by conceptualizing the concerned theories, it has been possible to hypothesize six hypotheses. On statistical verification through PLS-SEM analysis, all these hypotheses have been supported. The exogeneous independent variables LON, PEN, DEP, PEU and PU impact on the AOP significantly that in turn impacts QL, the goal of this study. Of course, the impact of AOP on QL appears to be strong but negative in nature as the concerned path coefficient is -.49 with level of significance $p<0.001$(***). Among the effects of the exogeneous variables on AOP, the effect of impact on AOP by PU is the maximum as the concerned path coefficient is 0.52 with level of significance $p<0.05$(*). In this study, we have separately considered the effects of two moderators age and gender on the five linkages which are LON→AOP (H1), PEN→ AOP (H2), DEP→AOP (H3), PEU→AOP (H4) and PU→ AOP (H5). So far as impacts of the moderator Age on these five linkages are concerned, the impact of the moderator Age on the linkage PEU→AOP (H4) is the highest as the concerned path coefficient is 0.46 with the level of significance $p<0.01$(**). So far as effects of the moderator Age on the other four linkages are concerned, it appears that the effects are all significant as

the concerned path-coefficients are 0.21 (p<0.05) for the linkage LON→AOP (H1), 0.32 (p<0.05) for the linkage PEN→AOP (H2), 0.39 (P<0.01) for the linkage DEP→AOP (H3) and 0.27 (p<0.001) for the linkage PU→AOP (H5). So far as effects of the other moderator, Gender are concerned, it appears that this moderator has the highest effect on the linkage DEP→AOP (H3) as the concerned path coefficient is the highest and it is 0.47 (p<0.05). So far as coefficients of determinant are concerned, it appears that LON, PEN, DEP, PEU and PU can simultaneously explain AOP to the extent of 52% since the concerned R^2=0.52. Moreover, the AOP can explain the QL (goal of this study) to the tune of 71% as the concerned R^2=0.71. The explanative power of the model is 71% which is considerably high.

5   Discussion and key findings

Feelings to be alone or to be separated is instrumental with the concept and feeling of forlornness. It arises because of having inadequate societal relationship. This concept gives rise to the feelings of loneliness. The study hypothesized that the loneliness impacts addiction of online platforms and it has been supported by statistical validation. This concept has been supported by earlier studies (Tomaka et al., 2006; Yang & Lin, 2014). This study hypothesized that perceived enjoyment positively impacts addiction of online platforms which has been validated through statistical analysis. This concept received sanction from earlier studies wherein it has been envisaged that enjoyment is conceptualized as an extent to use a technology which is thought to be enjoyable regardless of any performance consequence that may be anticipated (van der Heijden, 2003). Depression, being a special mental status of individuals, has an effective impact on addiction of online platforms as is clear from the validated hypothesis H3. This concept has been supplemented by earlier studies (Jeon & Jang, 2014) where the study analysed the conduct of some Korean students. It highlighted that if the students suffer from depression, they are forced to be intimately involved in a frequent use of technology. This they do to be relieved from depression. This eventually leads to addiction in that technology. Perceived ease of use and perceived usefulness both impact on addiction of online platforms as has been transpired from this study (H4 and H5). These two constructs are the core constructs of Technology Acceptance Model (Davis et al., 1989) and many studies subscribed that these two beliefs have a considerable impact on use of a technology and such use of technology eventually gets the users addicted to that technology (Taylor & Todd, 1995; Lee et al., 2007; Arpaci et al., 2018; Sulaiman et al., 2019). Studies reveal that addiction of online platforms negatively impacts quality of life. This has too received support from earlier studies (Kingpadung & Phusavat, 2010).

Now we shall discuss how age and gender affect (as moderators) the addiction of online platforms through the five exogeneous predictors LON, PEN, DEP, PEU and PU impacting AOP. This covers the linkages concerning to H1, H2, H3, H4 and H5. First, the effects of age of the users on these five linkages will be analysed. In this analysis, we shall categorize the two age groups of the online users, one is young adult (18-35 years), and another is med-aged adult (36-55 years). This idea has been lent from Cameron (1969) as already mentioned earlier. The effects will be discussed graphically. We shall analyse the effects of the two age groups of the users in the five linkages arising out of the predictors-addiction linkages covering H1, H2, H3, H4 and H5. The presentation has been projected here through five separate graphs, collectively marked as Figure 3.
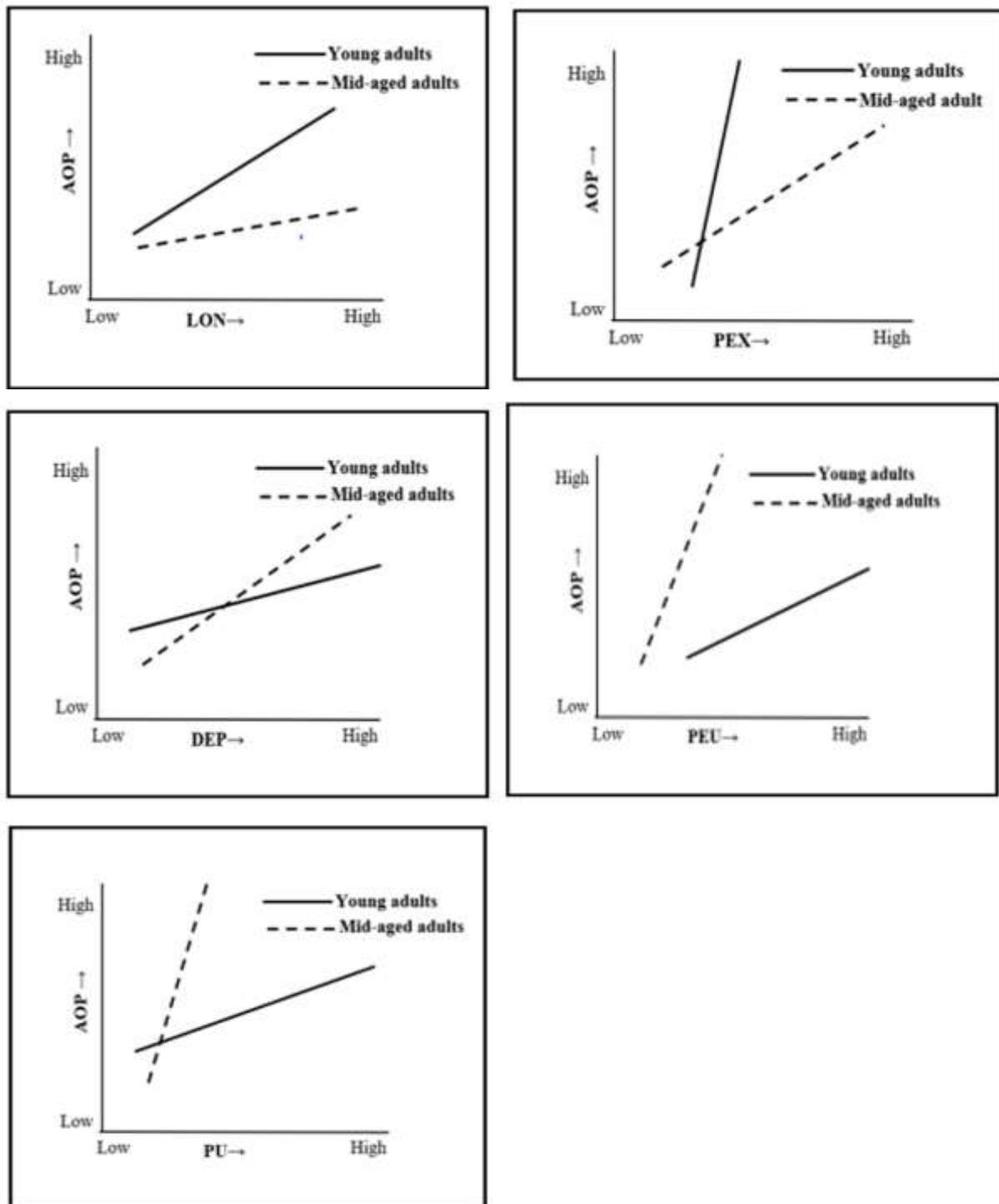
Figure 3: Effects of addiction by the moderator, Age

We shall discuss the effects of age through two categories which are young-adult and mid-aged adult on the different linkages LON→AOP, PEN→AOP, DEP→AOP, PUE→AOP and PU→AOP in a brief way. This has been shown through five graphical representations. In each graph, the continuous line represents young-adult character whereas dotted line represents mid-aged character. With increase of loneliness, the increase of addiction affinity is more for young adult compared to the mid-aged adult as the gradient of the continuous line is greater compared to that of the dotted line. Young adults are more prone to addiction with the increase

of feelings of loneliness. Same is the situation when effects of young-adult users and mid-aged adult users are studied relating to effects of perceived enjoyment (PEN) on the addiction of online platform (AOP). Here, it appears that with increase of feelings of perceived enjoyment, the rate of young-aged users' affinity for addiction to online platforms increases more compared to the case of mid-aged adults since the dotted line representing mid-aged adult character bears less gradient compared to the continuous line representing the case of young adults. But effects of age in two categories as moderators on the DEP→AOP (H3) linkage show a reverse result. Here, sense of depression is seen to have affected much on the mid-aged adults. That is why the dotted line representing mid-aged adults character bears greater inclination (higher gradient) compared to the continuous line representing the case of young adults. The mid-aged adults are found more sensitive to depression compared to young adult. Similarly, the effects of age on the PEU→AOP (H4) linkage show that with increase of ease of use, the mid-aged adults become more addicted compared to young adults. Easiness affects in such a way as with feelings of easiness, the young adults do not exhibit much addictive affinity like mid-aged adults. Same is the case when age acts as a moderator on the PU→AOP (H5) linkage. Dotted line representing the nature of mid-aged adults bears greater gradient showing that with increase of PU, the rate of increase of AOP is more for mid-aged adults in comparison to young adults. We shall now discuss the effects of Gender as a moderator in the five linkages covering H1, H2, H3, H4 and H5. Here, obviously two categories of gender have been considered, male and female. These are shown in different graphs collectively marked as Figure 4.
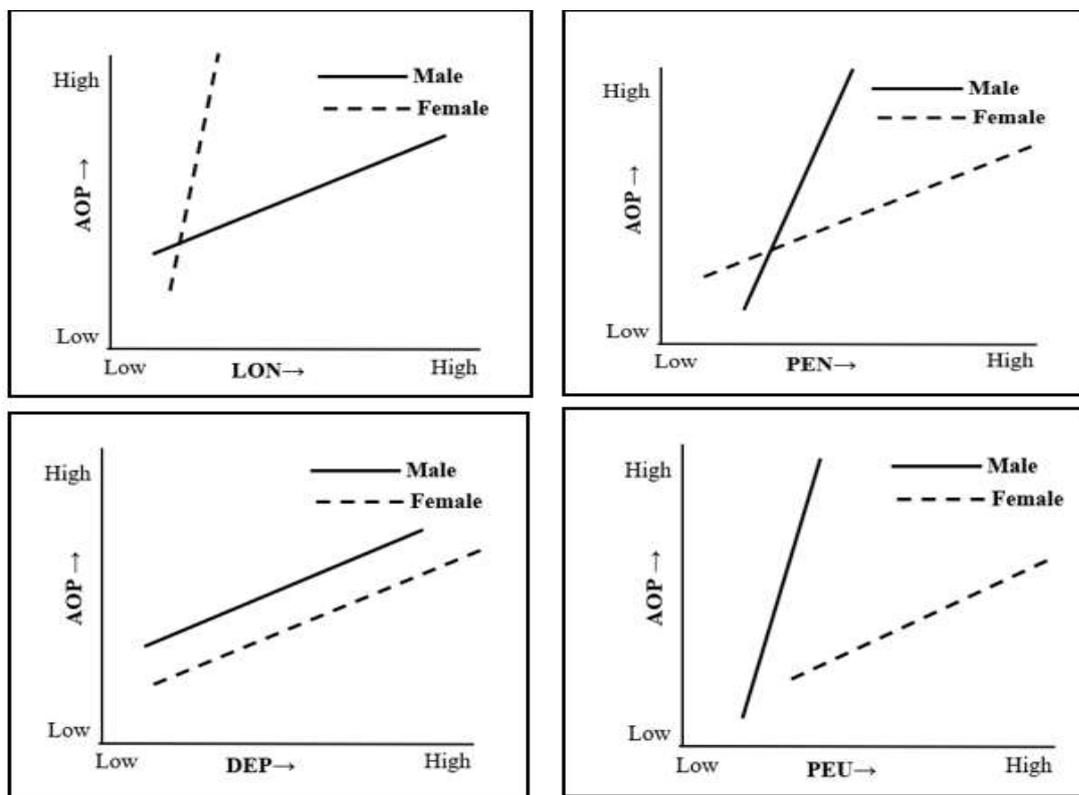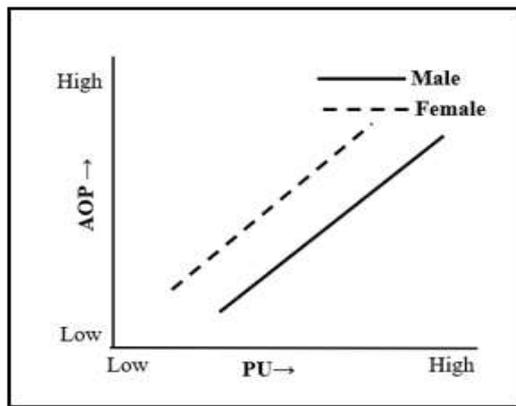
Figure 4: Effects of addiction by the moderator, Gender

The continuous lines in all the graphs represent the effects of male whereas the dotted lines in all the graphs represent the effects of female in this context. So far as effects of loneliness in addiction of online platforms are concerned, it appears that with increase of feelings of loneliness, the rate of addiction is increased for female more compared to male as the gradient of the dotted line is greater than the gradient of the continuous line. The situation is reversed while considering the effects of Gender moderator on the PEN→AOP (H2) linkage. Here, with increase of Perceived Enjoyment (PEN), the rate of growth of addiction for male is more compared to female as the gradient of the continuous line is greater than the gradient of the dotted line. Interestingly, in case of effects of Gender moderator on DEP→AOP (H3) and PU→AOP (H5) linkages, the situation appears to be almost identical. The rate of increase of addiction tendency with increase of feelings of depression and perceived usefulness remains the same for male and female and that is why these two graphs represent almost two parallel lines. Again, with increase of PEU, the rate of increase of AOP appears to be more in case of male compared to female as the gradient of the continuous line is greater than the gradient of the dotted line.

5.1 Theoretical contributions

This research study could yield an enriched and comprehensive theoretical understanding by bringing connection between loneliness, perceived enjoyment, depression, perceived ease of use and perceived usefulness with addiction of online platforms. This theoretical model has been able to provide effective inputs as to how the addiction of online platforms adversely affects the quality of life of individuals and how the age and gender factors moderate the impacts of different predictors on the addiction of online platforms. The theoretical model has been developed lending inputs from some addiction theories. There are many theories, but, from those theories, Adult Attachment Theory, Tension Reduction Theory and Technology Acceptance Model have been selected to identify successfully the factors affecting the addiction of online platforms. This is a specific theoretical contribution of this study. Moreover, to identify the predictors of addiction of online platforms, we did not consider many factors, but selected some better suited specific factors with the help of the already mentioned theories. By selecting such antecedents, it was possible to achieve 71% explanative power of the model. This is also considered as one of the theoretical contributions of this study. By selecting two core constructs (perceived ease of use and perceived usefulness) of acceptance model, it has been possible to include many vital beliefs since perceived ease of use includes self-efficacy, simplicity and compatibility (Yi et al., 2009) whereas perceived usefulness

includes some other vital determinants like performance, trust, effectiveness, risk perception and productivity (Turner et al., 2010). Hence, by inclusion of these two beliefs, it has been possible to consider at least eight vital factors. This is also considered as one of the important theoretical contributions of this study. This study also included one exogeneous factor perceived enjoyment. This belief has been included in the extended Technology Acceptance Model as is transpired from the other studies (van der Heijden, 2003). Consideration of this belief (Perceived Enjoyment) is claimed to have strengthened the performance of the model. This may also be construed to be another theoretical contribution of this study. Moreover, consideration of two moderators, Age and Gender towards their impacts on the predictors-addiction linkages could strengthen the model by achieving its explanative power as high as 71%. This is also claimed to be another theoretical contribution of this study.

5.2 Practical Implications

This study has highlighted that excessive usage of online platform by the users brings addiction to it. It affects the quality of life of the users adversely. Addictive users cannot control their behaviour towards repeated usage of a technology (Hong et al., 2012). Hence, the policymakers are needed to take appropriate actions towards developing the sense of the addicted users of online platforms. This would help to control their usage habits. It will help them not to be eventually addicted in the online frequent usage activities. The policy makers also have the responsibilities to structure appropriate policies that would restrict the users to use online platforms frequently. This may be done by limiting their usage for a certain specific period per day. This could restrict the habit of the online users not to use online platforms frequently. It would help the users not to be addicted to it. It has been observed in other studies that for restricting addiction to smartphones, which is considered as one of the online platforms, an app has been developed (Ko et al., 2015). The authority should take initiatives to provide a devise or otherwise in this line to restrict the users to use excessive other online platforms that could cause addiction detrimental to the quality of life.

In brief, the authority is needed to think how the self-controlling skills of the users towards using online platforms can be developed. To achieve this, the authorities needed to take appropriate steps to frame implementable and consistent regulations for restricting the frequent usage of the online platforms. This would help the users not to be addicted in using online platforms. It eventually deteriorates the quality of life. Addiction is a menace to the society. Awareness among the users of online platforms is required to be grown regarding the dark sides of addiction of the online platforms. For this, the authority is needed to conduct awareness programs frequently with regular interval. This awareness program is considered vital. Addiction is related with such a behavioural trait of an individual that the individual can hardly control themselves even knowing its inimical consequences. Hence, development of awareness among the users of online platforms is perceived to be an effective treatment of this ailment.

5.3 Limitations and future scope

All the research studies have some limitations. Likewise, this study has also some limitations. In the validation stage through PLS-SEM analysis, survey was conducted considering the respondents from metropolitan and semi-urban areas. No respondents were considered from rural areas. But presently, even in all developing countries, online usage has become ubiquitous and it has spread in almost all areas regardless of their nature. Non consideration of respondents from rural areas does not project the result in a generic form. In the survey, we

used the feedbacks of 320 respondents. This is inadequate to represent the whole society. Inputs of people from all categories possessing varied socio-economic status ought to have been considered. The model provided could achieve 71% explanative power. Ideally, to make it near to 100%, we could have considered inclusion of other boundary conditions in this model which has not been done in our study. Thus, it is seen that there are many limitations of this study. It is expected that the future researchers would take up these uncovered issues to give this study a full proof shape.

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Appendix 1:

Measurement instruments

Constructs	Sources	Research Instruments
Loneliness (LON)	Tomaka et al., 2006; Wei et al., 2005; Yi et al., 2012; Yang & Lin, 2014; Chatterjee, 2020	LON1: I consider online platforms as the only option for me to have a conversation with my friends, colleagues, and relatives.
		LON2: Most of the time in a day, I remain completely isolated.
		LON3: I do not have any companionships to talk.
		LON4: I like to be alone with different online platforms.
		LON5: I feel uncomfortable to meet a person physically.
Perceived Enjoyment (PEN)	Ven der Heijden, 2003; Lee & Tsai, 2010; Shin, 2010; Wei & Lu, 2014; Sarin et al., 2020	PEN1: I feel good to connect with my friends online instead of physically.
		PEN2: I enjoy online shopping very much.
		PEN3: I like to spend maximum amount of time using social networking sites.
		PEN4: I feel good by chatting with my friends and colleagues via online platforms.
		PEN5: I am fond of playing online video games.
Depression (DEP)	Kim et al., 2007; yi et al., 2012; Yeo et al., 2014; Wang, 2019; Gong et al., 2020	DEP1: I do not find any pleasure to do things.
		DEP2: Most of the time I feel depressed for want of physical contacts with others.
		DEP3: I find it very difficult to concentrate on things like reading books, playing games etc.
		DEP4: I often feel tired to do things.
		DEP5: I do not find any interest of experimenting new things.
Perceived Ease of Use (PEU)	Davis et al., 1989; Taylor & Todd, 1995; Bisen & Deshpande, 2018; Sulaiman et al., 2019; Chatterjee et al., 2020b	PEU1: Use of online platforms is easier to learn and apply.
		PEU2: It is easier to use different online applications like online shopping, online games, social networking etc.
		PEU3: All the online platforms are flexible to use.
		PEU4: People can be engaged with different online activities as they have smartphones.
		PEU5: I do not need any particular training to use different online platforms like social networking, online shopping, playing online video games etc.
Perceived Usefulness (PU)	Davis et al., 1989; Lee et al., 2007; Kwon et al., 2013; Jiang et al., 2014; Arpaci et al., 2018	PU1: I shall be more efficient if I use different online platforms for different purposes.
		PU2: Most of the online platforms are inexpensive to use.
		PU3: I find use of different online platforms beneficial for me.
		PU4: I can get all the information by using online platforms on a real-time basis.
		PU5: I can buy things sitting at my home using shopping websites.
Addiction of Online Platforms (AOP)	Hong et al., 2012; Park & Lee, 2012; He et al., 2019	AOP1: I use different online platforms for more than 12 hours a day.
		AOP2: I find it quite difficult to physically communicate with people.
		AOP3: Because of my frequent online activities, I do not get enough sleep.
		AOP4: I cannot remain offline for more than 30 minutes at a stretch.
Quality of Life (QL)	Costanza et al., 2008; Kingpadug &	QL1: My productivity has gone down because of overuse of different online platforms.
		QL2: I spend less time talking with my family members.

	Phusavat, 2010; Whiteside et al., 2018	QL3: I cannot remember easy things.
		QL4: I am always busy with online activities and thus do not get time to exercise.