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Attitude, Self-Control, and Prosocial Norm to Predict Intention to Use Social Media Responsibly: From Scale to Model Fit towards a Modified Theory of Planned Behavior

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Abstract: Severe abuse of social media has currently become a threat to social sustainability. Although "responsible use of social media" has recently attracted academics' attention, few studies have investigated the psychosocial antecedents of individuals' intention to use social media responsibly (IUSR). Therefore, the current study tested whether attitudes, self-control, and prosocial norms (ASP) can positively and significantly predict social media users' IUSR. To this end, the theoretical interrelationships among ASP were explored, and an initial pool of items was developed by reviewing the relevant literature. Then, the items were selected based on a panel of experts' content validity test. An online questionnaire was used to survey university student social media users (n = 226) in Bangladesh. PLSc-SEM and CB-SEM bootstrapping, followed by an artificial neural network (ANN) analysis, were completed to evaluate the measurement and structural models. Current results show that the three elements of ASP strongly correlate with and significantly influence each other, but attitude and prosocial norms partially mediate the relationships between the antecedents and intention. The predictors in the proposed model substantially predict and explain IUSR, which is supported by results of relevant past studies in different disciplines. Thus, the model expresses its applicability as a modified theory of planned behavior (TPB) in researching individuals' social media behavior. The study has implications for relevant stakeholders to take crucial measures to promote more responsible use of social media. Limitations and avenues for future study are also presented.

Keywords: social media; attitudes; self-control; prosocial norms; behavioral intention; responsible social media users; young generation; structural equation modeling (SEM); theory of planned behavior (TPB); artificial neural network (ANN).

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1. Introduction

Social media is considered one of the top research subjects in the social sciences (and beyond) [1]. Social media was created by the people and exists for the people [2]. However, its scope has been expanding quickly from a connectivity base, and user-generated content-sharing platform [1], to a system of information aggregation [3–6] or a needs satisfier, with multiple interactive aspects for people with various backgrounds [2]. Thus, social media has become a persistent channel of mass personal communication [3–5]. Social media has acquired an intensive attachment by many people, but its digital flexibility toward human interactions [1,3] makes it a common platform for antisocial activities [7–9]. Therefore, regarding social sustainability, a wake-up call is needed for responsible use of social media.

In the current context, the responsible use of social media means using social media as an ethical and accountable user, producer, or consumer [10,11] and adequately understanding the purposes of digital use, communicated content, and the impact of one's social media interactions [12] to avoid problematic or addictive use [13,14] or abuse (harm), while being proactively involved in prosocial usage (e.g., caring conduct toward others, doing good) [5–7]. By problematic or addictive use of social media, the current study refers to social media users' unhealthy or extreme engagement on social media platforms, which demonstrates a lack of control regarding certain types of continued behavior over time [13,14]. These types of behavior bring detrimental or clinically impairing consequences, or related disorders, for the social media user's psychological, personal, professional, and social-level functioning [13,14]. The current study assumes that social media abuse is any form of verbal, informational, physical, or sexual violence that occurs between any users and any psychological/emotional abuse perpetrated online, intended to bully, harass, stalk, or intimidate any targets through the use of texting, depressive symptoms, sexting, or any other means [15–18].

Social media abuse can be any form of misinformation sharing, such as spreading fake news or manipulating news on social media [18–20], without providing sufficient effort to evaluate whether there will be appropriate or harmful consequences of such conduct [19,20]. The negative consequences of social media abuse may add challenges to human communication efforts, produce tension, and enhance misunderstanding or disbelief, thus posing a threat to social sustainability [18]. Moreover, by severe abuse, this study refers to social media users' engagement in actions that lead to severe online and offline consequences, including family break-ups, job quitting, and suicidal actions by the victims [21–23]. Severe abusive actions may include, but are not limited to, attributional (specific or globally negative) comments [24], rumors, conspiracy, automation, online harassment [18], cyber-dating violence [15,16], cyber-bullying, sextortion/sexting, revenge porn, catfishing, scamming [25], religious abuse [26], and radicalism [22].

The current study assumes that responsible use of social media may impact social sustainability, which is a pluralistic rather than an abstractly defined concept, based on some interdependent social pillars [27–34]. These pillars include individual and community well-being, social cohesion, social equity, social inclusion, social justice, diversity, social capital, civic engagement, collectivism, place attachment, safety and security, eco-prosumption, health, competency, and prosociality [27–34]. Such concepts may apply equally to virtual and physical spaces as people have started valuing virtual space as an alternative to physical space [32–37].

The current study is concerned with the lack of responsible use of social media in Bangladesh [21–23,38,39], which is an emerging economy [40] and is currently emphasizing the digital revolution to connect more people to the development process [41]. Due to the rapid penetration of the internet, Bangladesh is currently one of the top ten countries in the world in terms of internet users [22,42,43], with 30 million young people [44] out of the total 45 million social media users, which comprises 27.2% of the total population and has increased by 25% between 2020 and 2021 [45]. However, although young people (ages 19–24) use social media as a critical source of information [45], they are also the most problematic social media users [38–41], and their addiction rate is 28.6% compared to older users (23.5%) [42].

Although Facebook is the most popular social networking site, it is vastly misused [46]. It has become an infodemic of propaganda and misinformation [23,41] and a platform of unethical activism [47], pornography, gambling, excessive video gaming [38], radicalism [41], sexual harassment, and cyberbullying [21]. However, such activities are currently triggering massive online and offline chaos [21,23]. While this is the current scenario of social media abuse in Bangladesh, no substantial efforts have been made to promote responsible use of social media [21–23]. Moreover, few studies have been conducted to understand the psychosocial factors of responsible online behavior [7]. Therefore, the present study aims to fill this gap by investigating the structural interrelationships between a couple of underresearched psychosocial determinants of social media users' responsible behavioral intention using the theory of planned behavior (TPB) framework [48,49]. Specifically, the current study is interested in testing whether attitudes (ATT), self-control ability (SCA), and perceived prosocial norms (PPN) can significantly predict social media users' behavioral intention to use social media responsibly (IUSR). Many researchers in the social and behavioral sciences previously tested such a modification in the TPB framework [50–55]. First, the researchers were motivated to add contextual components to the original TPB framework as it is an open theory that can incorporate additional or modified predictors if the new components strongly correlate with each other and explain a significant proportion of variance in "intention" [48,49,56,57]. Second, stronger attitudes, subjective norms, and perceived behavioral control (PBC) may not lead to a stronger behavioral intention to perform that behavior in all contexts [48–50].

Third, some studies on individuals' responsible behavior reported significant gaps between attitude and intention [58–60], subjective norms and intention [61,62], and PBC and intention in the past [63,64]. Therefore, considering other researchers' suggestions to fill those gaps in the TPB framework, the current study assumes that SCA and PPN may predict IUSR better than subjective norms and PBC. For example, SCA was recommended to add to the TPB framework to minimize the attitude-intention gap [64–66] as SCA significantly differed from PBC [67,68] and was associated with antisocial or unethical behavior negatively, whereas PBC was associated with such behavior positively [69]. More importantly, SCA is one of the most cited theories of crime [70,71], which may minimize the gaps between PBC and intention or intention and behavior as a mediator in predicting responsible/sustainable behavior of people [10,64,72,73].

Both good and bad social ties can stimulate subjective norms depending on how people perceive important others or what others expect from them [61,74,75]. Therefore, subjective norms can create a gap between norms and ethical behavioral intention [61,74,75]. Consequently, it can trigger both prosocial and antisocial behaviors [66,76]. However, PPN, by its root, is only associated with prosocial intention and suppresses antisocial stimuli [59,77,78]. Moreover, in terms of the interrelationships of the variables, PPN may highly correlate with SCA [57,58], and SCA may substantially correlate with ATT in a responsible behavior context. However, SCA and subjective norms may correlate negatively in similar contexts [65,79], or SCA may produce weaker or more potent effects on ATT than other antecedents in the model [80,81]. In most intention-behavior studies, ATT is commonly used and strongly predicts intention more than other antecedents in the TPB framework based on the structural model [73,82]. Therefore, the current study kept ATT as a base construct [83,84], but it added SCA and PPN to ATT as a modified TPB to predict social media users' IUSR. More specifically, the current study's objectives are to: (1) investigate the interrelationships among ATT, SCA, and PPN from the perspectives of responsible use of social media; and (2) to explain the effects of ATT, SCA, and PPN on IUSR.

This investigation is essential in the current context to significantly enhance our understanding of the psychosocial factors of adopting responsible behavior on social media. In contrast, the insights have several implications for the relevant stakeholders to develop various measures to motivate more responsible use of social media before young people become obsessed [85,86]. The current study's findings may contribute to forming policies for enhancing social sustainability in Bangladesh and other parts of the world. So far, research on "responsible behavior offline" has significantly contributed to formulating policies for environmental or economic sustainability in the material society [58–60]. Thus, research on "responsible behavior online" is expected to generate insights into benefiting the stakeholders toward social sustainability. This is due to the fact that virtual spaces have become a vital living space for individuals [32–37] where the potentiality for harmful behaviors by the users is ample as the potentiality for prosocial behaviors [6,10,87]. However, responsible use of social media may create excellent work and living spaces to peacefully lead the social media users' lives [30,32].

1.1. Literature Review and Hypothesis Development

1.1.1. Responsible Use of Social Media

Social media was founded as a medium for open and honest communication so that friends or colleagues would converse or commiserate with one another [12]. However, currently, social media is being heavily abused [7,46]. Online abuse or offensive social media behaviors are harmful actions that violate personal or property rights and norms to harass others [88]. Such behaviors are usually caused by users' aggressive or addictive attitudes to social media, moral disengagement, and the influence of bad companies [89]. Although the perception of responsibility on social media varies between persons, improper or irresponsible usage carries significant risks for all stakeholders [6]. Therefore, motivating social media users to be responsible online can be treated as one of the current societal challenges of digitalization [90].

Responsibility may derive from accountability as it causes people to think about their actions more carefully [10]. However, the feelings of not being accountable may magnify the likelihood of actual cyberbullying behaviors [91], as someone lacking accountability may increase conformity to aggressive peers' behaviors [10]. Therefore, it is crucial to realize not only the consequences of inappropriate usage [92] but also the consequences of prosocial usage of social media, which refers to meeting social expectations for online etiquette in all types of interactions [92] and promoting positive behavior (e.g., helping others) wisely in or outside of one's online community [93].

Researchers define online prosocial behavior as voluntary behavior carried out in an online context that maintains excellent and harmonious relations inside and outside someone's online community [94]. Prosocial behaviors may include comforting others, sharing information or intellectual resources, helping victims, liking socially desirable and widely acceptable posts, and sending someone a kind message for a social cause to benefit others [94]. So far, a few studies have measured social media users' antisocial and prosocial behavior. For example, some researchers [87] conducted a review of publications published between 2014 and May 2021 and found that only a few papers measured the relationship between social media use and intention for online prosocial behavior. Other researchers measured the effect of the emergency perception of bystanders of cyberbullying victims on helping tendencies based on the mediating effect of state empathy and feelings of responsibility to help [95]. Moreover, it was found in the literature that a positive attitude to avoid excessive attachment to social media is the essential intervention for preventing internet addiction [96]. A few researchers also explored that affective and cognitive empathy, and moral disengagement is related to purposeful social media use [89].

In the past, it was also found that negative civil and hateful comments led to social media users' negative attitudes toward prosocial behavior online and offline targeting of refugees [97]. In contrast, one of the previous studies surprisingly found that both positive and negative emotions caused prosocial and antisocial behaviors [98]. Both were positively correlated, and their associations were mediated by adolescents' social and audio-visual media use but not by gaming or functional internet use [98]. However, none of those previous studies quantitatively investigated the effect of PPN on social media users' online behavior. In contrast, only a few studies without any experiment recommended that developing and maintaining PPN in online communities may prevent cyberbullying [99]. For example, bystanders can be influenced by PPN to facilitate the victims promptly online [100].

1.1.2. Theory of Planned Behavior and its Modification

TPB [48,49] is one of the most cited theories in social science, particularly in explaining human behavior [49,101]. Its interaction with theories in other disciplines is growing, such as information and communication or information technology adaptation theories [49,50,83]. TPB originated from the theory of reasoned action (TRA) [49]. The TRA and the extended TRA, as the TPB, are cognitive theories, and both present the conceptual framework to forecast people's behavioral intentions and thus predict their likelihood of engaging in that behavior [102]. According to TPB, attitudes toward a specific behavior, subjective norms regarding that behavior, and PBC influence intentions to perform that behavior, and ultimately those intentions influence actual performance (actions) [49,101]. Several studies have verified the causal relationships between the variables in the TPB framework based on the outcomes of regression or structural equation modeling analysis of the self-reported data [101,102].

Although initially, it was assumed that the constructs in the TPB are based on the assumptions of sufficiency [49], it was later found that attitudes, subjective norms, and PBC poorly predicted intentions and behaviors in different contexts [50,83]. For example, the extant literature explored the possibility that TPB may neglect the affective components of attitude and count only personal beliefs [50,103]. In contrast, personal beliefs could not predict behaviors properly in many contexts, whereas emotional control and informational management could do so [50,103]. After a series of experiments, researchers have claimed that new conceptual predictors can be added to the traditional antecedents in the TPB framework if such additional/modified predictors can explain a substantial proportion of variance in "intention" [48,57].

1.1.3. Intention

A review of over 50 years of research papers on the psychology of human behavior reveals that "intention" is one of the most widely used constructs to predict behavior [104]. "Intention" means a person's willingness (i.e., be sure/confirm) to perform a specific behavior that predicts actual behavior almost accurately in normal conditions [105]. A person's "intention" to do a particular behavior also explains why and how that person engages in that behavior [101]. So, it is treated as the most direct and closest predictor of actual behavior [83], as 13 meta-analyses of intention-behavior research showed that intention and behavior are substantially correlated ($r = 0.495$) [84]. Studies found that "intention" has the most significant effect on actual behavior in a structural model with various situational predictors of behavior [101]. So, the more robust the "intention", the more likely the behavior may follow [49,65]. Therefore, it is a reasonable assumption that "intention" is the immediate antecedent or proximate behavior [49]. However, a person's intention always depends on some antecedents or predictors [49,104].

1.1.4. Attitude

ATT is the most researched construct in cognitive, psychological, or behavioral sciences to predict intention and behavior [48,49]. ATT determines behavioral beliefs about a particular behavior [102]. Alternatively, it is a kind of enduring evaluation of the person, objects, or issues [106]. ATT clarifies the appraisal of behaviors or posits itself between the degrees of favorable and unfavorable feelings or judgments of an entity [48]. ATT could be very general (e.g., attitude toward coffee) or very specific towards personally performing a behavior (i.e., getting coffee with Mr. X. at a local coffee shop) [104]. Therefore, a person with substantial positive ATT towards a specific behavior is more likely to perform that behavior [102]. However, in a structural model, ATT can successfully predict different types of responsible human behavior [83,102]. It is also the most robust predictor among the other antecedent variables of behavioral "intention" in the TPB framework [73,82].

1.1.5. Perceived Behavioral Control Versus Self-Control

PBC is the belief in the ability or mastery to perform a behavior [72]. As a performance regulator, PBC is based on the capacity to perform and autonomy/feelings of freedom to perform [69,107]. It does not consider the consequences of conducting a behavior before it is performed [107]. Therefore, in situations when people have less information than required to understand the consequences of behavior or when changes happen in the requirements or resources to perform a behavior, or when people need to enter into new and unfamiliar situations quickly with a chance of higher correspondence between PBC and actual behavioral control, PBC predict behavioral intention very loosely [108]. Such situations may frequently appear on social media [64]. However, to overcome the pitfall of such situations, researchers have urged to emphasize SCA on social media, which is an essential attribute of individuals faced with temptations [109]. Gottfredson and Hirschi's self-control theory says that low or lack of individual SCA is a significant predictor of offensive or antisocial behavior [110–112]. SCA can divert an individual's attention from something immediately desired to a better goal by altering emotions, holding back certain impulses and guiding for improvements [109].

Researchers defined SCA as one of the most significant personal controllable dimensions, including the ability for behavioral control, cognitive control, and decisional control (e.g., controlling thoughts, emotions, impulses, performance, and habits) [110–115]. So, the operational definition of SCA includes everything people could do to steer their behaviors toward the desired end state by delaying instant gratifications or exchanging smaller rewards but monitoring and adapting the situations to receive a greater reward in the future [116]. As with other personality traits, SCA is an open system that can be influenced by the environment at any age of human being throughout the lifespan [117] due to the salient developmental tasks that emerge and change across the lifespan (e.g., academic achievement in adolescence) [118]. SCA might be reduced over time, but it is adaptive or potentially renewable to some extent as a function of relative practice, whereas its strength extends throughout the process of self-regulation to enable people to control their behavior in multiple domains [119]. So, with a lack of SCA, people may act against their better judgment [5].

People need a certain degree of SCA either in an individualistic context to pursue a personal goal or in a collectivistic context to fit into the community's cohesion for a better society [68]. Individuals' display of prosocial behavior and avoidance of antisocial behavior requires a higher degree of SCA to override selfish impulses/emotions [120]. Researchers also found that PBC is positively associated with alcohol and drug abuse, whereas higher SCA is negatively associated with them in a social context where such conduct is treated as antisocial [69,121]. Also, studies found PBC as a non-significant predictor of intention to engage in a prosocial Facebook campaign [82]. Therefore, SCA might be assumed as a more appropriate predictor of intention than PBC in the context of responsible behavior.

1.1.6. Subjective Norms Versus Prosocial Norms

Subjective norms are the estimates of social pressure [122]. Subjective norm is derived from people's feelings about what they should do by observing other important actors (e.g., family, friends, or co-workers) in the social environment or their beliefs about what other important actors expect from them [49,65,104]. A key feature of subjective norms is the desire to conform to a group with the tendency to use minimum efforts due to the impression of the societal values attached to that group, even when a group is ill-motivated [75]. From these perspectives, it is reasonable to assume that subjective or group norms have both good and bad orientations [59,104], as researchers of economics, sociology, and social psychology have theoretically and experimentally explored their existence [61,75]. Previous studies also found that deviant peer norms were positively associated with deviant behaviors [79], as affiliation with deviant peers activates antisocial norms [59,120,123].

A social media user can do anything on social media as their friends do without providing substantial efforts to evaluate the right or wrong of their conduct [74]. For example, users can share misinformation or rumor on social media within or beyond their close networks due to the strength of their social ties with ill-motivated peers [74]. Therefore, destructive norms deviant from welfare orientations are more likely to persist even in a larger group in the short term, although they may disappear in the long run [74]. For example, it was found that subjective norms are positively associated with students' behavioral intention to plagiarize [65].

Studies found that close or socially matching peers' norms predicted alcohol consumption [76]. Although a positive and significant relationship was found between attitudes, ability, and intention, no positive relationship was found between social norms and intention to avoid "illegal mining" [124]. In contrast, the deficit in the capacity to activate PPN may increase antisocial behavior [59,77,78]. PPN are the specific ethical standard, beliefs, and behavioral guidelines that people can learn and adapt to increase the well-being of other individuals or groups [59]. For example, antisocial behavior can be constrained through reciprocity, social responsibility, altruism, volunteerism, or other prosocial interactions [77,78]. PPN, with collective efficacy, may facilitate moral communities, enhance social bonding, increase prosocial interactions, and decrease antisocial interactions or behaviors [59,77,78]. Moreover, it was found that subjective norms negatively correlate with ATT and SCA [65], whereas PPN was positively associated with SCA in an ethical behavior context [120]. Therefore, people's PPN is assumed to be a more appropriate predictor of intention than subjective norms in the context of responsible behavior.

1.1.7. Interrelationships among Attitudes, Self-Control, and Prosocial Norms

In the past, it was found that ATT and SCA were positively correlated but negatively associated with behavioral intention to plagiarize [65]. However, SCA might have been shaped by attitudes toward the desired goal or the correct allocation of efforts to perform a behavior [125]. It was found that poor SCA or self-control deficit directly affected athletes' antisocial behavior, but SCA was mediated by social interactions with peers [126]. Prosocial ties were positively associated with higher SCA but negatively associated with low SCA, whereas antisocial ties were strongly associated with lower SCA than higher SCA in an experiment where college students' close friends were associated with heavy drinking [127]. Self-regulation plays a vital role in translating PPN into action (i.e., self-regulation mediates the relationships between PPN and intention) [128]. However, Kabiri et al. [126] found that SCA was mediated by favorable attitudes to academic dishonesty when someone associated with deviant peers and perceived low constraint to deviant behavior.

Also, higher SCA may mediate the direct relationship between PPN and intention [129,130]. People with high trait SCA who demonstrated more compliance with prosocial peers led more positive ATT toward COVID-19 vaccinations and were more likely to modify vaccination intention and behavior to help others in the community [80]. However, those researchers urged to investigate whether the exertion of SCA can produce weaker or more robust effects on attitudes in a different context [80]. Overall, the literature reviewed shows that attitudes, self-control ability, and prosocial norms can correlate, affect and mediate their interrelationships with each other and relations with "behavioral intention" in different contexts. So, the current study proposes the following hypotheses in the context of responsible use of social media:

H1a: Attitudes, self-control ability, and perceived prosocial norms are significantly and positively related to each other.

H1b: Attitudes, self-control ability, and perceived prosocial norms can directly, positively, and significantly influence each other.

H1c: Attitudes can mediate the relationships between SCA and IUSR, and PPN and IUSR; self-control ability can mediate the relationships between PPN and IUSR, and ATT and IUSR; perceived prosocial norms can mediate the relationships between ATT and IUSR, and SCA and IUSR.

1.1.8. Attitude and Behavioral Intention

Most behavioral theories in social science propose that attitude guides behavior [49] indirectly through its influence on "intention," so, conceptually, attitude is an antecedent of intention [104]. Several metanalyses showed that attitude is the most researched predictor of "intention" [49]. Individuals with a positive attitude towards a particular behavior are more likely to have a positive intention to perform that behavior [102]. For example, it was found that social media users' attitudes to marketing activities of a sustainable/ethical brand affect their intention to purchase that brand on social media [131]. Customers' attitudes to value co-creation predict intention to co-create value on social media [132]. So, the current study proposes the following hypothesis:

H2: Social media users' positive ATT to the responsible use of social media is significantly and positively associated with their IUSR.

1.1.9. Self-Control and Behavioral Intention

SCA is the active regulation of one's thoughts, feelings, and behavior and is strongly associated with reducing negative behaviors and promoting positive behaviors [117]. SCA has the potential to bring more order, structure, and coherence into an individual's life [133]. People with various degrees of SCA show variations in their behavioral intentions to engage in socially desirable or undesirable behaviors [66,80,116,134]. Individuals with higher SCA exhibit fewer deceptive or unhealthy behaviors such as substance abuse than individuals with lower SCA [69,121]. Higher SCA is positively associated with higher life satisfaction [119] or the perception of positive meaning in life [133]. Also, in the past, quantitative investigations found a direct positive association between SCA and the adoption of pro-environmental behavior [63], whereas a negative association between SCA and intention to plagiarize was found [65]. So, the current study proposes another hypothesis as follows:

H3: Social media users' SCA is positively and significantly associated with their IUSR.

1.1.10. Prosocial Norms and Intention

In the responsible behavioral context, PPN is a more appropriate predictor than the subjective norm as the latter may not trigger prosocial behavior online as normative beliefs about cyber aggression predict aggressive cyber behavior, as aggression is more acceptable and tolerable when it occurs online than offline context [135]. In contrast, PPN is only directed toward what is socially desirable or acceptable, so it may trigger only prosocial behavioral intention by suppressing antisocial stimuli [59,77,78]. Researchers conceptually developed PPN as a positive youth development construct [136]. PPN is generalized via empathic feelings from one behavior to another [77]. Individuals' attachment to a prosocial community generates more prosocial behavioral intention [128] due to prosocial conformity and refined interventions for promoting such behaviors. [77]. So PPN explores prosocial peers that may provide protective influences and support for victims [137].

It was found that PPN is a predictor of minimizing social risks of interactions (i.e., lower victimization but higher prosocial friendship) with peers both in novel and existing contexts [100]. Therefore, online PPN may be a powerful counterweight against producing cyberaggression [138]. It can induce people's social connectedness, improve relationship quality, foster well-being and self-esteem, or bring positive outcomes in their relational and societal domains [94]. However, some researchers have urged to explore more insights into the activation of PPN and suggested testing PPN as a predictor of behavioral intention outside the Western context [139]. Therefore, the current study proposes one more hypothesis:

H4: Social media users' PPN of responsible use of social media is positively and significantly associated with their IUSR.

Based on the theoretical interrelationships of the variables, the following hypothetical model is drawn (see Figure 1).

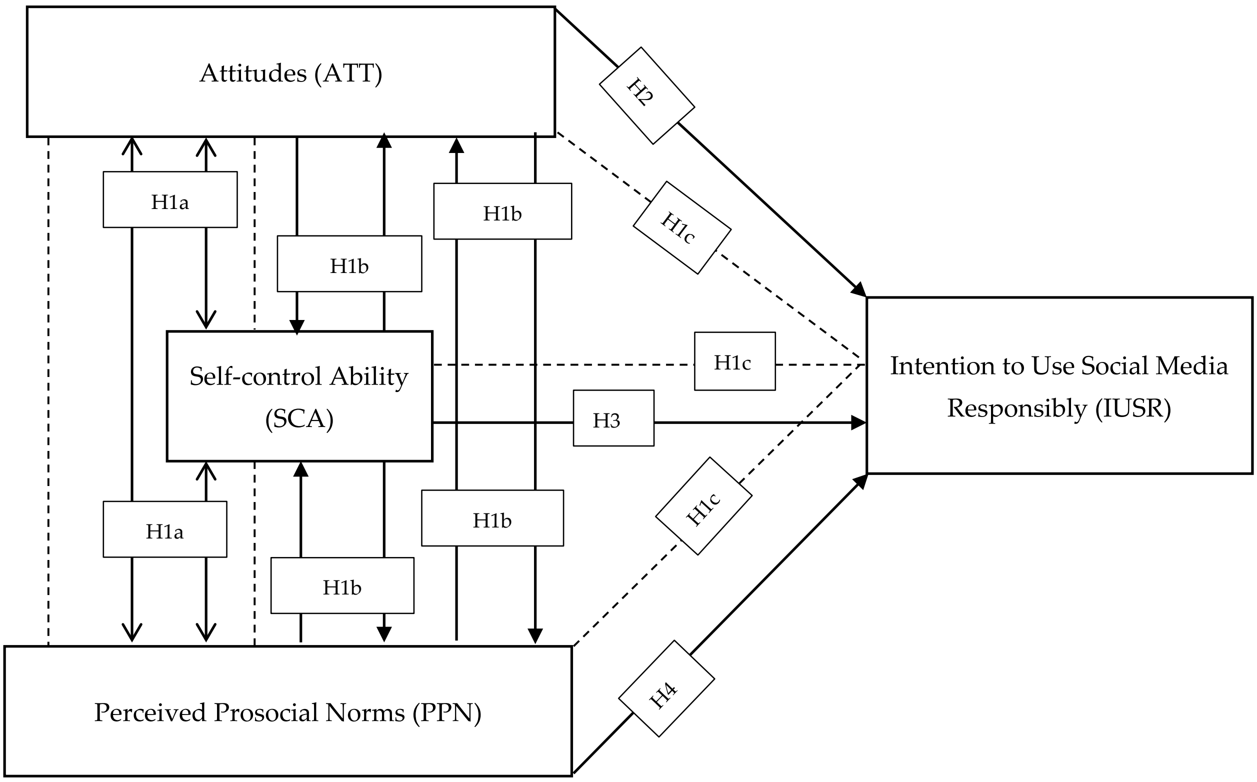

Figure 1. Hypothetical model of the study: **------** refers to the mediated paths, →refers to the direct paths, ↔refers to the correlated paths.

2. Materials and Methods

2.1. Identification of Items, Face Validity, and Experts' Content Validity

Due to a lack of abstract scale in social media literature to measure ASP, the current study followed a systematic process for scale development (see Figure 2 for the detailed research process). Then, it followed the SEM procedures to analyze the collected data [140–143]. At first, the researchers identified an initial pool of domain-specific items by reviewing a few related research papers. Then to ensure the items' ability to reflect on what they are intended to measure, the researchers checked the face validity of the items [144–150] by five students (three male and two female) studying Information Systems at a public university in Bangladesh. The validity checking form included only the constructs' definition and the items to ensure a bias-free selection of the items [147,149–154]. The participants associated the items with their respective constructs by marking them as yes/no [147]. However, three items from each of the SCA, PPN, and IUSR domains were non-representative (See Table 1 for results of face validity and content validity test).

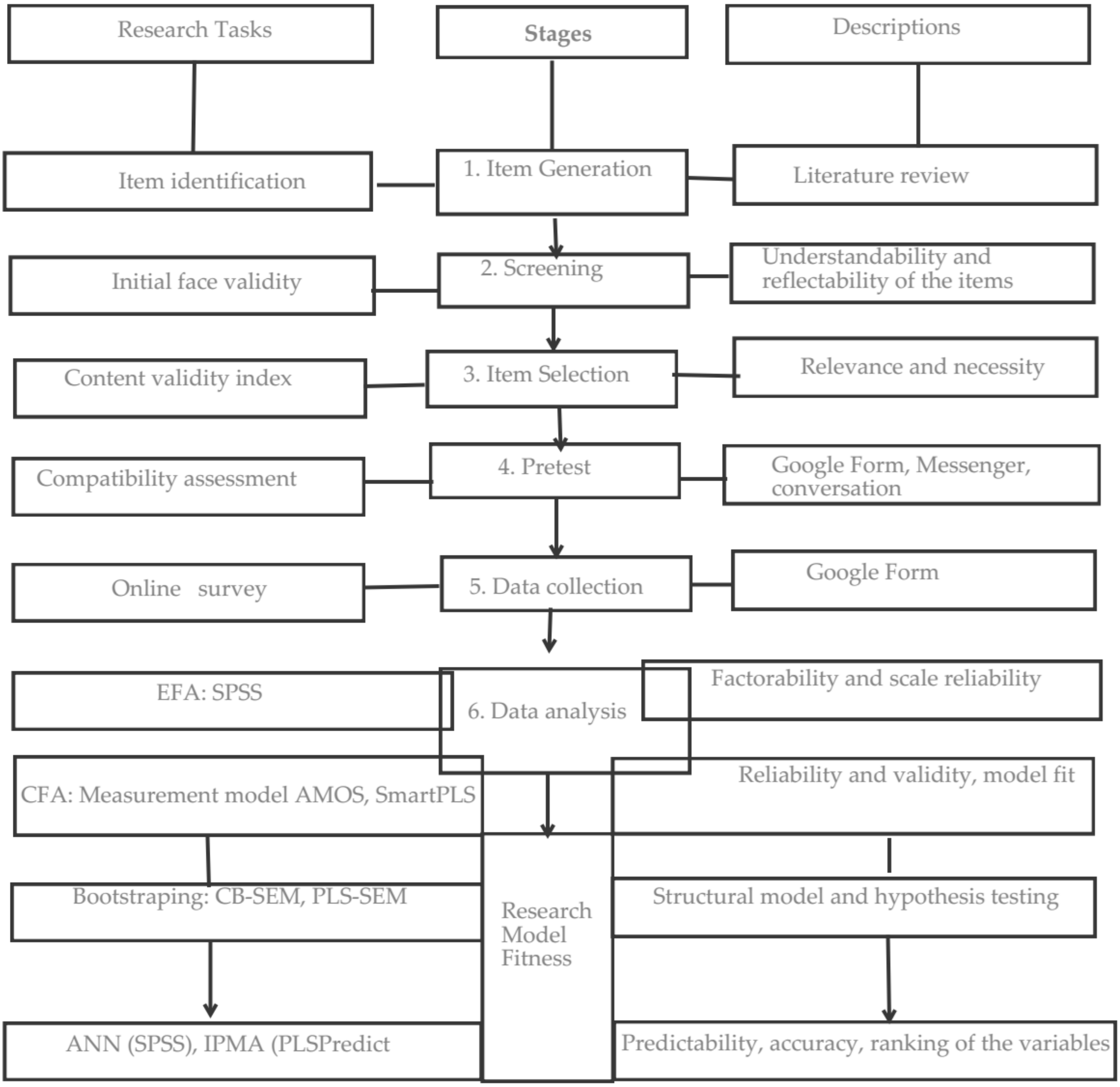

Figure 2. The research flowchart.

Table 1. The initial pool of items and the items retained after the face validity and content validity tests

Code:	Item Description (Used as a Statement in the Questionnaire)	Sub-Themes	Initial Face Validity: Majority 1 or 0	Experts' Content Validity: I-CVI, Kappa, CVR	Scale S-CVI/U, S-CVI/Avg	Retained or Not I-CVI ≥ 0.83; Kappa > 0.74; CVR ≥ 0.99	References
Theme/construct 1: Attitude to use social media responsibly (ATT)							
ATT1	If I avoid problematic use of social media, that will enhance my effectiveness online.	Cognitive	1	1,1,1	0.83, 0.94	√	[96]
ATT2	I like to present myself online as someone making positive choices.	Affective	1	1,1,1		√	[155]
ATT3	My favorite places online are where people are respectful to each other.	Behavioral	1	1,1,1		√	
ATT4	Teasing or making fun of others online with comments is enjoyable to me.	Affective	1	1,1,1		√	[96,156]
ATT5	Although I am not in face-to-face contact with others, I cannot do whatever I like on social media.	Cognitive	1	1,1,1		√	
ATT6	I should work continuously on raising awareness about online violence and its consequences	Behavioral	1	0.66, −4.33, 0.33		X	[157]
Theme/construct 2: Self-control ability to use social media responsibly (SCA)							
SCA1	I need to be good at resisting temptation on social media	Restraint	1	1,1,1	0.75, 0.95	√	[158,159]
SCA2	I need to refuse things to do on social media that are bad for me and others	Performance	1	1,1,1		√	
SCA3	Sometimes I cannot stop myself from doing something unexpected on social media due to situational factors, even though I know it is wrong.	Emotions	1	0.83, 0.81,1,		√	
SCA4	I wish I had more self-discipline.	Thoughts	1	1,1,1		√	
SCA5	I lose my temper pretty easily and can't control myself on social media	Emotions	0	N/A		X	[160,161]
Theme/construct 3: Perceived prosocial norms for the use of social media responsibly (PPN)							
PPN1	I am emphatic with those who are in trouble with social media-related issues.	Emphatic	1	1,1,1	1,1	√	[162]
PPN2	I intensely feel what others feel in good deeds.	Good feelings	1	1,1,1		√	
PPN3	I feel the necessity to support those who are the victim on social media	Helping	1	1,1,1		√	
PPN4	I immediately sense my friends' discomfort online, and even they do not directly communicate with me.	Sorrow-feelings	1	1,1,1		√	

PPN5	My friends think that it is essential that I always use social media to get in touch	Close norms	0	N/A		X	[163]
Theme/construct4: Behavioral intention to use social media responsibly (IUSR)							
IUSR1	I can guarantee that I will always justify before posting/sharing/commenting on any photos/videos/texts so that it does not go in the wrong way or embarrass others	Perfection	1	1,1,1	0.80, 0.96	√	[10,94,155]
IUSR2	I can guarantee that I am not intended to share or add arguments to rumors on the internet.	Non-disturbance	1	0.83, 0.81,1		√	[94,155]
IUSR3	I am intended to use social media for creative learning and sharing (e.g., posting, sharing/reading, writing, seeing photos or flyers, watching videos) about positive social, cultural, or religious issues.	Creative	1	1,1,1		√	[41,64,155]
IUSR4	I will console and support those victimized or who experienced any hardship online.	Helping	1	1,1,1		√	[80,95,164]
IUSR5	I am intended to guide my friends on how to use the internet more efficiently/acceptably	Mentoring	1	1,1,1		√	[155,165]
IUSR6	If I get something wrong with me on social media, I am not intended to do something wrong	Kind	0	N/A		X	[94,163]

Note: √ = an item retained for the next step, whereas X means the item is removed.

The selected items in the face validity test (i.e., 19 items: See Table 1) were sent to a panel of six experts (two female and four male) of social science disciplines (Journalism and Mass Communication, Anthropology, History and Archaeology, Islamic Studies, and Political Science). The content validity form consisted of definitions of the domains and instructions to measure CVI (i.e., a 4-point scale ranging from 1 = not relevant to 4 = highly relevant) and CVR (3-point scale ranging from not necessary = 1, useful but not essential = 2, and essential = 3) [150]. However, as the content validity index (CVI) ignores the inflated values that may occur due to the possibility of chance agreement (Pc), the Kappa coefficient was calculated using the formula [Pc = [N! /A! (N − A)!] × 0.5 N.; K = (I-CVI − Pc)/(1 − Pc)] as used in the previous studies to understand content validity better [150,151]. Also, to eliminate unnecessary items for operating a construct among the selected items, the content validity ratio (CVR) was calculated [150,151]. For selecting an item from the CVI test, this study considered the values of I-CVI ≥ 0.83, CVR ≥ 0.99, and kappa > 0.74, as suggested by researchers [150,151]. As the S-CVI/U scores decreased with the increase of experts, S-CVI/avg values were also calculated, and a value of 0.8 was considered acceptable [152]. However, only one of the attitudinal items was removed due to low I-CVI and CVR scores, and finally, 18 items were retained to measure the four domains, including ATT, SCA, PPN, and IUSR.

2.2. Questionnaire Design and Pretest

In the past, several studies conducted surveys after face validity and content validity tests without pilot tests [153,154]. However, the current study designed a small-scale pretest with 12 participants to assess the compatibility of the survey (i.e., whether the target respondents face any difficulties in using the online survey form and whether the items and instrument function well) [144–147]. Previous studies supported such a pretest design with a small sample of 10 [166], 12 [167], or 20 participants [168]. The participants were approached using one-to-one Facebook Messenger conversation. No distortions were noticed at the pretest stage, so no change was made in the final questionnaire.

A self-administered online questionnaire was designed using the Google Form, which was easier to connect with web browsers, search engines, and social media platforms [169]. Google Form is a free-of-cost survey tool [170] and offers facilities for a comprehensive survey [171]. Google Form-based survey offers efficiency and protects fidelity without sacrificing quality and security as it is easy to download the forms and get the data in CSV file format, which is useable for diversified statistical analysis [170]. As the demography of the survey participants was not the study's primary concern, only three items, including respondents' gender, daily social media usage rate, and primary social media, were measured with a categorical scale (see Table 2). However, with one reverse coded question, a seven-point Likert scale (i.e., ranges from strongly disagree = 1 to strongly agree = 7) was used to measure the items related to the constructs in the proposed conceptual model. All of the questions in the questionnaire were compulsory so that no respondent could submit the form with missing responses, which on the one hand, reduced the researchers' job of handling the missing data issues, on the other hand, increased the validity of the responses.

Table 2. Social media users' profile in the studied sample.

Mostly Used Social Media		Gender		Description of the Daily Usage of Social Media	
	%	**Category**	**%**	**Category**	**%**
Pinterest	0.9	Male	71.8	30 min	2.6
Instagram	1.8	Female	28.2	30–60 min	7.0
Twitter	2.2			60–90 min	21.1
WhatsApp	3.5			90–120 min	18.1
YouTube	10.6			120–150 min	11.9
Messenger	5.3			150–180 min	15.4
Facebook	75.8			180–210 min	23.8
					Mins
				Mean	141.24
				Std. Deviation	53.09
				Range	180.00

Note. min = Minutes. The usage class's upper limit was considered in calculating the descriptive statistics.

2.3. Sample and Data Collection

The study followed the sample size justification criteria for determining the sample size, including the G*power test (i.e., a priori power analysis to test whether certain effect sizes can be statistically rejected with a desired statistical power) [172–174]. Then, participants per parameter or predictor ratio (to have an estimate with a desired level of accuracy while the research question focuses on the size of a parameter) [e.g.,171,210], ten times rules (sample larger than a structural path towards particular latent constructs or the number of formative indicators) [175–178], resource constraints, [174], and the sample size used in recent publications/literature in the related disciplines were considered [174]. For example, several recently published studies used sample size less than 300, including studies on problematic/addiction (n = 229) [179], social media overload effects [177], social media users' psychological wellbeing (n = 176) [180], psychological ownership on social media (n = 222) [178], social media participation during COVID-19 pandemic (n=236) [181], cyberbullying (before and during pandemic: n = 173, 181) [156], and bystanders behavior (study 1, n = 150, study 2, 287) [95]. However, many researchers stated that if a variable has three or more items, a sample size of 100 is enough for convergence [182]. The required sample size for the current study was 74, according to the G*power test (i.e., with $f^2 = 0.15$, $\alpha = 0.05$, 1-β error Prob. = 0.95 while applying the multiple linear regression, fixed model, single regression coefficient statistical test from the t-test family) [172,173].

The researcher (i.e., a university faculty at a public university in Bangladesh) attached the Google form-generated invitation link on their personal verified Facebook page and Messenger while approaching different student groups. The Facebook friends were requested to share the link in their academic networks so that more and more respondents are connected conveniently with the snowball effect. The study purposefully used a few filtering questions, such as the respondents should be 18 years old, Bangladeshi citizens, current university students, and regular social media users. According to previous studies, such a cohort of social media users are heavy users in Bangladesh [23,38–42] and are assumed to be educated and conscious of current societal problems [41]. However, from March to April 2022, from over 2000 student-Facebook friends of the researcher, 226 responses were recorded. The current sample size (N = 226) was sufficient to conduct SEM analysis as it was substantially more than required [174,183] and met the criteria of normal distribution [141,184,185]. Moreover, the current study has addressed the sample size-related issues by applying consistent partial least square structural equation modeling (PLS-SEM), covariance-based structural equation modeling (CB-SEM) of 5000 subsamples bootstrapping [186–189], and artificial neural network (ANN) approaches in analyzing the data [190–192].

2.4. Data Analysis

After collecting the data, a comma delimited (.csv) file was downloaded from Google drive, where Google Form-based data were located, and then transmitted to Excel (.xlsx) and SPSS (.sav) file format for analysis. SPSS 25 was used for descriptive statistics, scale reliability, exploratory factor analysis, and ANN analysis [193,194].

After analyzing the descriptive statistics of the social media user's profile, the internal consistency reliability of the items, including corrected item-total correlations, squared multiple correlations (SMC), and Cronbach's α (i.e., the inter-item consistency), were checked against the cut-off criteria suggested by the experts [193,194]. Then CB-SEM analysis [140,141,145–148] using SPSS AMOS 21 [140,141] and PLSc-SEM analysis using SmartPLS 3.3 [142,143] were carried out. Common method bias (CMB) tests, including Harman's single-factor analysis [195], latent variable correlation matrix [196], detail multicollinearity assessment using variance inflationary factor (VIF) [155], and marker variable test [197,198], were carried out to address social desirability related issues derived from the single survey [195]. Then the measurement and structural model's results based on the bias-corrected and accelerated complete-bootstrapping of 5000 subsamples [185,199] were compared to verify if any of the values of path coefficients (β/t-values), reliability, validity, predictability, or model fit significantly higher or lower than the lower or upper bound values of 95% confidence interval (CI) [143,189,199].

Finally, for robustness, as the SmarPLS software does not provide the GoF (Global goodness of fit), it is calculated using the formula (i.e., the average R^2 of the endogenous latent constructs and the geometric mean of the average communality) suggested by the researchers [168,200,201]. Moreover, PLSpredict and ANN analyses were conducted to rank the variables based on importance and performance scores [168,202]. ANN is remarkably an analogous scattered processor that consists of simple processing units (i.e., consisting of an input layer, one or more hidden layers, and an output layer) having a natural predisposition for keeping storage of experimental knowledge and making it available for use (similar to the human brain) by gaining knowledge from its surrounded environment through a learning process [168,192,203].

The current study trained the neural network by selecting the multilayer perceptron (MLP) algorithm with Sigmoid activation function for both hidden and output layers [191,192,204] and by allocating 90% of the sampled data for the training procedure and the remaining 10% data for the testing procedure using a ten-fold cross-validating procedure to obtain the root mean square of errors (RMSE) [168,191,192,204]. Four ANN models were created based on the number of significant paths between the variables found in CB-SEM and PLS-SEM [191,192]. Finally, the sensitivity analysis of the ANN models was conducted to determine each predictor's relative importance and normalized significance, which was calculated by dividing its relative importance by the maximum importance expressed in percentage [168,191,204].

3. Results

3.1. Social Media Users' Profile

The user profile of the participants (See Table 2) shows that Facebook is the most used social media by young people in Bangladesh (75.8%), followed by YouTube and WhatsApp. The majority of the respondents are Male (71.8%). Most university student social media users use social media daily between 150 minutes and 210 minutes.

3.2. Results for the Measurement Model

For all of the items, the squared multiple correlations (SMC: $r > 0.30$) and corrected item-total correlations ($r > 0.5$) are higher than the experts' suggested values (see Table 3) except for IUSR2 and ATT4, which were therefore eliminated before EFA to ensure convergent validity of each item [194,205]. No items are found to correlate too highly (i.e., $r > 0.80$), but their higher Cronbach's α ensure excellent internal consistency reliability [189,205]. Moreover, for all of the constructs, the KMO is (Kaiser-Meyer-Olkin measure of sampling adequacy) > 0.8, and the considerable value calculated by Bartlett's test of sphericity indicates that the correlation matrices for the items are not identity matrix (i.e., higher χ^2 = 396.616, 476.236, 535.049, 459.361; df = 6, $p < 0.001$), which ensures the appropriateness of the data for exploratory factor analysis using principal axis factoring [206,207].

The data were not substantially different from the normality as skewness (i.e., <−2) and kurtosis (<4) values are within the experts' recommended threshold [141,184,185,188]. In addition, the normality test's results are also satisfactory using ML bootstrapping with 5000 subsamples [186,187]. The correlations between the domains and total scores are significant ($p < 0.05$) [207]. All of the dominant constructs (Eigenvalues > 1) explain more than 50% of the indicator's variance in EFA (see Table 3), and the item loadings are >0.708 both in EFA and CFA, indicating excellent reliability [189,205,208].

Table 3. Indicators' statistics (item-wise statistics).

Constructs (CA)	Code	Mean [a]	SD [a]	CIT [a]	SMC [a]	KMO, BTS-χ^2. df = 6 ***	Eigenvalues [a]	Variance explained [a]	LEF [a]	LPLS [b]	VIF [b]	LCB [c]	Sig [bc]
ATT (0.857)	ATT1	6.03	1.028	0.678	0.550	0.822, 396.616	2.422	60.540%	0.745	0.740	1.874	0.742	***
	ATT2	6.04	1.023	0.656	0.509				0.717	0.710	1.765	0.713	***
	ATT3	6.01	0.961	0.731	0.665				0.814	0.815	2.198	0.815	***
	ATT5	6.08	0.955	0.743	0.697				0.831	0.842	2.287	0.835	***
SCA (0.881)	SCA1	6.07	1.050	0.718	0.606	0.835, 476.236	2.622	65.554%	0.774	0.788	2.084	0.778	***
	SCA2	6.00	1.106	0.769	0.689				0.838	0.805	2.496	0.830	***
	SCA3	5.92	1.240	0.718	0.606				0.773	0.792	2.074	0.778	***
	SCA4	6.02	1.119	0.776	0.723				0.850	0.851	2.583	0.850	***
PPN (0.892)	PPN1	6.13	1.037	0.782	0.717	0.832, 535.049	2.725	68.132%	0.844	0.827	2.674	0.847	***
	PPN2	6.08	1.080	0.720	0.772				0.891	0.822	3.198	0.803	***

	PPN3	6.02	1.135	0.684	0.568				0.724	0.870	1.880	0.754	***
	PPN4	6.00	1.106	0.774	0.679				0.835	0.776	2.622	0.824	***
IUSR (0.879)	IUSR1	6.09	1.026	0.709	0.754	0.834, 459.361	2.586	64.660%	0.783	0.774	2.124	0.777	***
	IUSR3	6.15	0.983	0.786	0.723				0.822	0.866	2.331	0.843	***
	IUSR4	6.11	0.997	0.721	0.715				0.775	0.793	2.076	0.782	***
	IUSR5	6.05	1.084	0.728	0.764				0.835	0.791	2.418	0.811	***

Note: ^{a} = Values are generated by SPSS 25. ^{bc} = Values are generated based on bias-corrected and accelerated (BCa) bootstrapping of 5000 samples by SmartPLS 3.3 and AMOS 21, respectively. *** = $p < 0.001$. SD = Standard deviation. CITC = Corrected item-total correlations. SMC = Squared multiple correlations. KMO, BTS = Kaiser-Meyer-Olkin Measure of Sampling Adequacy, Bartlett's Test of Sphericity. LEF = Loadings based on principal axis factoring. LPLS = Loadings based on PLSc-SEM. LCB = Loadings based on CB-SEM. VIF = Variance inflationary factor.

As the VIF <3 (see Table 3) for all of the indicators, collinearity is not an issue [189,208]. The values of Cronbach's α (CA > 0.70: 0.85–0.91), composite reliability (CR > 0.70: 0.85–0.89 ≠ 0.95), average variance extracted (AVE > 0.50: 0.60–0.68), Heterotrait-Monotrait Ratio (HTMT: ranged 0.662–0.810 ≠ 0.90), and the values of Fornell Larcker criteria in the measurement model (see Table 4) are within the threshold for reliability and validity of the data [143,189]. Furthermore, these values generated by PLSc-SEM and CB-SEM based on the bootstrapping of 5000 samples are higher than the lower bound values (5% CI) but lower than the upper bound values (95% CI), showing outstanding internal consistency reliability, convergent validity, and discriminant validity of the model [189,205–209].

Table 4. Measurement model's reliability and validity.

	Internal Consistency Reliability (PLSc-SEM/CB-SEM *)		**Convergent validity (PLSc-SEM/CB-SEM *)**	**Discriminant Validity (PLSc-SEM)**				
				HTMT/FLC	ATT	PPN	SCA	IUSR
Constructs	CR	CA	AVE	ATT	0.778 ^{F}			
ATT	0.859/0.859	0.857/0.874	0.610/0.605	PPN	0.658/0.658 ^{F}	0.822 ^{F}		
SCA	0.882/0.884	0.881/0.898	0.654/0.655	SCA	0.659/0.657 ^{F}	0.703/0.706 ^{F}	0.809 ^{F}	
PPN	0.891/0.896	0.891/0.900	0.675/0.684	IUSR	0.778/0.778 ^{F}	0.801/0.803 ^{F}	0.808/0.807 ^{F}	0.804 ^{F}
IUSR	0.882/0.879	0.880/0.918	0.655/0.646					

Note: * = Calculated based on the formula given by Fornell and Larcker [163]. HTMT = Heterotrait-Monotrait Ratio. FLC = Fornell-Larcker criteria. ^{F} = Fornell-Larcker values.

The data are free from the common method bias (CMB) problem [189,193–199,205]. First, according to the outcome of Harman's single-factor analysis, one factor explains only 47.45% variance instead of more than 50% [195]. Second, latent variable correlations (see Table 5) between the independent latent variables (exogenous variables) are strong (r < 0.90) and significant at $p < 0.001$ [189,196,205], Third, according to the detail collinearity statistics, the VIF (variance inflationary factor) are <3.0 for all of the constructs [189]. Fourth, the marker variable test's results (i.e., 'media exposure,' which is not a part of the current study but is used in the researcher's full project) the common factor counts on only 28.09% variance (i.e., <50%) in the model [197,198].

Table 5. Results for the structural model.

PLSc-SEM/CB-SEM Structural Model Results										
Constructs	LVC	VIF	Predictability		Path Coefficients					Decisions on Hypotheses *
			R^2	Q^2	*t* /CR	β	5% CI	95% CI	*p*	
ATT→IUSR	0.779/0.782	2.029	0.810/0.804	0.640	2.688/4.642	0.319/0.342	0.162/0.185	0.562/0.587	0.004/0.002	Supported
PPN→IUSR	0.808/0.783	2.296			2.323/4.195	0.344/0.308	0.128/0.108	0.604/0.586	0.011/0.015	Supported
SCA→IUSR	0.810/0.802	2.290			2.142/4.833	0.355/0.368	0.103/0.118	0.646/0.665	0.020/0.015	Supported
PPN→ATT	0.666/0.652		0.534/0.504	0.360	2.092/4.257	0.395/0.388	0.082/0.107	0.691/0.682	0.018/0.033	supported
SCA→ATT	0.661/0.651				2.146/4.137	0.379/0.385	0.095/0.128	0.681/0.668	0.016/0.016	supported
ATT→SCA	0.661/0.651		0.563/0.543	0.430	2.416/4.083	0.327/0.354	0.107/0.119	0.563/0.568	0.008/0.017	supported
PPN→SCA	0.712/0.686				3.556/5.363	0.499/0.455	0.272/0.240	0.711/0.711	0.000/0.000	supported
ATT→PPN	0.666/0.652		0.564/0.544	0.427	2.275/4.231	0.338/0.357	0.083/0.094	0.574/0.589	0.011/0.036	Supported
SCA→PPN	0.712/0.686				3.485/5.304	0.492/0.454	0.278/0.234	0.724/0.721	0.000/0.000	supported

Note: * = $p < 0.05$.

3.3. Results for the Structural Model and Hypotheses Test

The R^2 (see Table 5 and Figure 3 for SEM results) of IUSR as produced by PLSc-SEM/CB-SEM (0.810/0.804) indicates a substantial explanatory power or excellent in-sample predictability of the model [189,210]. The same is true for ATT (0.534), SCA (0.563), or PPN (0.564), as all of their antecedents explain more than 50% of their variances when they are used as endogenous mediator variables. Also, the Q^2 for the IUSR with an omission distance of 10 (D) is 0.640, indicating the PLS path model's substantial predictive accuracy [155,171]. Although ATT (0.360) has a medium, SCA (0.430) and PPN (0.427) have medium to a large predictive accuracy in the model [189,210].

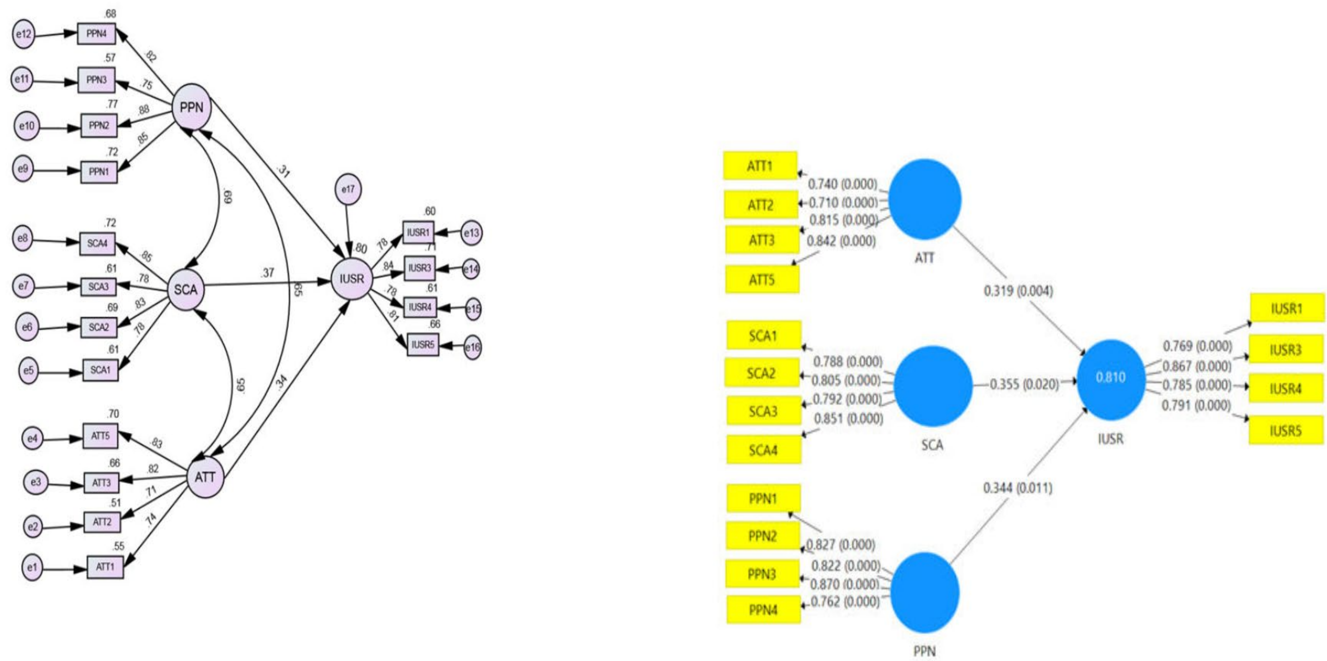

Figure 3. The model on the left is the structural model based on CB-SEM, and the model on the right is the structural model based on PLSc-SEM. Alternative and mediation models are not shown here (see Tables 5 and 6 for the detailed results). Note: The models are the original outcome as produced by AMOS 21 and SmartPLS 3. CB-SEM output by AMOS doesn't give 0 before a decimal, for example the indicator loading of ATT1 is read as 0.74 but it is shown as in the figure as .74.

The strong correlations are reported between the latent variables (r < 0.90, $p < 0.001$), which ensure that the current data supports the H1a (i.e., attitudes, self-control ability, and perceived prosocial norms are strongly positively related to each other). Second, the path coefficients (*t* and β values) (see Table 5 and Figure 3) for all of the direct paths to IUSR (i.e., ATT → IUSR, PPN →IUSR, SCA→IUSR) or paths among the predictors (PPN→ATT, SCA→ATT, ATT→SCA, PPN→SCA, ATT→PPN and SCA→PPN) are positive and statistically significant ($p < 0.05$). That means that all of the independent variables directly influence the dependent variables. So, H1b (i.e., attitudes, self-control ability, and prosocial norms can positively and significantly influence each other), and H2, H3, and H4 (i.e., attitudes, self-control ability, and perceived prosocial norms are positively and significantly associated with social media users' IUSR) are supported. However, in the case of mediation: H1c (ATT can mediate the relationships between SCA and IUSR, and PPN and IUSR; SCA can mediate the relationships between PPN and IUSR, and ATT and IUSR; PPN can mediate the relationships between ATT and IUSR, and SCA and IUSR) is partially supported as only PPN →ATT→ IUSR and SCA→ PPN →IUSR paths are found statistically significant ($p < 0.05$) (see Table 6). Moreover, the current study finds neither any significant changes in the path coefficients nor the model-fit indices due to the effects of gender and daily social media usage rate on the target variable (i.e., IUSR), so they remain as control variables in the model [194,211].

Table 6. Results of mediation analysis.

	Mediation Analysis: PLS-SEM/CB-SEM					
Constructs	**Path Coefficients**					**Decisions on Hypotheses ***
	t	**β**	**5% CI**	**95% CI**	***p***	
PPN→ATT→IUSR	1.769	0.121/0.133	0.036	0.271	0.038	Partial mediation
SCA→ATT→IUSR	1.538	0.124/0.132	0.026	0.299	0.062	No mediation
PPN→SCA→IUSR	1.625	0.182/0.168	0.021	0.370	0.052	No mediation
ATT→SCA→IUSR	1.601	0.117/0.130	0.014	0.252	0.055	No mediation
ATT→PPN→IUSR	1.428	0.122/0.112	0.022	0.280	0.077	No mediation
SCA→PPN→IUSR	1.911	0.166/0.143	0.063	0.341	0.028	Partial mediation

Note: * = β and *t* are positive and $p < 0.05$.

3.4. Model Fit

The values of the model fit indices (see Table 7 for results of PLSc-SEM and CB-SEM) of the current study meet the experts' suggested ideal threshold values (i.e., cut-off criteria) [186,189,209,212–215].

Table 7. Results for the model fit indices.

Model Fit Indices *												
PLSc-SEM					**CB-SEM**							
NFI	SRMR	d_ULS	d_G	SRMSR	NFI/PNFI	CFI/PCFI	TLI	GFI/PGFI	RMSEA	PCLOSE	CMIN/df	Bollen-Stine bootstrap *p*
0.920	0.033	0.149	0.174	0.038	0.931/0.760	0.968/0.791	0.961	0.916/0.660	0.059	0.145	174.76/98 = 1.783	0.190
GoF							0.725					

Note. GoF: The global Goodness of Fit. GFI = goodness of fit index. NFI = normed fit index. TLI = Tucker–Lewis index. CFI = comparative fit index. RMSEA = root means square error of approximation. SRMR = standardized root means square residual index. * = For CFA and structural model, the results are the same in CB-SEM.

The proposed model's CMIN/df < 3, GFI > 0.90, SRMR < 0.05, RMSEA < 0.08, TLI > 0.95, NFI > 0.90, CFI > 0.95 indicate it a good fit model [186,189,209,212]. Also, the values of the latest index offered in the SmartPLS [125], including d_ULS (i.e., 0.149 and d_G (i.e., 0.74), without having negative values in the upper and lower bounds of the 95% CI for the estimated and saturated models, claim a good fit model. The value of GoF (0.725 > 0.36: cut-off point) validates the predictive power of the proposed model as a whole, as recommended in the previous studies [168,200,201].

Furthermore, the values of parsimonious fit measures, such as parsimonious goodness of fit index (PGFI) > 0.50, parsimonious normed fit index (PNFI) > 0.50, and the value of the parsimonious comparative fit index (PCFI) > 0.50 indicate acceptable parsimony of the model [213]. In addition, according to the results of the Bollen-Stine bootstrap, the model fits better in 4050 bootstrap samples. It fits about equally well in 0 bootstrap samples, whereas testing the null hypothesis that the model is correct, the Bollen-Stine bootstrap probability, $p = 0.190$ (i.e., 19%) [214,215].

3.5. PLSpredict, Artificial Neural Network, and Importance-Performance Map Analysis

According to the output of the PLSpredict test by SmartPLS, none of the indicators' PLS-based values yields higher prediction errors in terms of RMSE (Root Mean Square Error) or MAE (Mean Absolute Error) compared to the LM (linear regression model)-based values, reflecting that the proposed model has a high predictive power/accuracy [175,216].

Artificial Neural Network (ANN) Analysis

Before assessing the ANN models, a linearity test with ANOVA (see Appendix A) was conducted to check the linear associations between the hypothesized independent and dependent variables, as suggested by previous studies [168,190,191,204]. The results illustrate that among the significant paths found in PLS-SEM and CB-SEM analysis, only one path (PPN * ATT) has a significant non-linear association (0.619). However, all of the remaining predictors (i.e., ATT * SCA, ATT * PPN, PPN * SCA, ATT * IUSR, SCA * IUSR, PPN * IUSR) have both significant linear and non-linear associations (i.e., $p < 0.05$) [191]. The ANN analysis (see Tables 8 and 9 for results and Appendix B for the diagrams) shows that the low mean RMSE values for training and testing for all of the models (testing values are between 0.046 and 0.089, whereas training values are between 0.067 and 0.198 respectively) along with very low standard deviation (between 0.005 and 0.27) indicating higher order of predictive accuracy and model fit [168,190–192,204,216].

Table 8. PLSpredict results.

Items	**PLS**		**LM**		**Difference between PLS and LM**		**Decision** [a]
	RMSE	**MEA**	**RMSE**	**MEA**	**RMSE**	**MEA**	
ATT2	0.9108	0.6331	0.9312	0.6534	0.0203	0.0203	High predictive power
ATT1	0.8982	0.6339	0.9079	0.6502	0.0097	0.0162	
ATT3	0.8112	0.5890	0.8326	0.5920	0.0214	0.0030	
ATT5	0.8056	0.6059	0.8316	0.6113	0.0260	0.0054	
SCA2	0.9173	0.5860	0.9396	0.6015	0.0223	0.0155	High predictive power
SCA1	0.8904	0.5890	0.8774	0.5916	−0.0130	0.0027	
SCA4	0.8872	0.5664	0.9100	0.5682	0.0228	0.0018	
SCA3	1.0353	0.6409	1.0689	0.6620	0.0337	0.0211	
PPN4	0.9395	0.6070	0.9606	0.6456	0.0211	0.0386	High predictive power
PPN2	0.8842	0.5307	0.8883	0.5517	0.0040	0.0211	
PPN3	0.8988	0.5869	0.9158	0.5694	0.0170	−0.0176	
PPN1	0.8544	0.5330	0.8698	0.5540	0.0154	0.0210	
IUSR4	0.7454	0.4393	0.7829	0.4705	0.0375	0.0312	High predictive power
IUSR3	0.6645	0.4289	0.6787	0.4303	0.0142	0.0014	
IUSR5	0.8061	0.4431	0.8445	0.4670	0.0384	0.0239	
IUSR1	0.7781	0.4551	0.8010	0.4614	0.0229	0.0063	

Note: [a] = Prediction errors in terms of RMSE (or MAE) for almost all indicators PLS < LM refers high predictive power [217,218].

Table 9. ANN analysis: the root mean square error values of the models.

RMSE								
	Model 1		**Model 2**		**Model 3**		**Model 4 (Combined Model)**	
	Input Covariates: SCA, PPN; Output: ATT		**Input Covariates: ATT, PPN; Output: SCA**		**Input Covariates ATT, SCA; Output: PPN**		**Input Covariates: ATT, SCA, PPN; Output: IUSR**	
ANN	Training	Testing	Training	Testing	Training	Testing	Training	Testing
1	0.1057	0.0987	0.1008	0.0664	0.1116	0.0922	0.0853	0.0463
2	0.9805	0.0962	0.1002	0.0869	0.1099	0.0853	0.0852	0.0447
3	0.1095	0.0892	0.1010	0.0606	0.1117	0.0689	0.1010	0.0690
4	0.1180	0.0725	0.1023	0.0636	0.1193	0.0985	0.0863	0.0572
5	0.1041	0.1006	0.1007	0.0500	0.1132	0.0656	0.0985	0.0892
6	0.1054	0.1039	0.1105	0.0865	0.1132	0.0573	0.0993	0.0775
7	0.1165	0.0572	0.1041	0.0554	0.1123	0.0714	0.0916	0.0863

8	0.1150	0.0742	0.1068	0.0571	0.1092	0.0889	0.0977	0.0727
9	0.1177	0.1108	0.1161	0.0753	0.1028	0.0593	0.0968	0.0524
10	0.1136	0.0945	0.1016	0.0710	0.1123	0.0856	0.0839	0.0608
Mean	0.1986	0.0898	0.1044	0.0673	0.1130	0.0770	0.0853	0.0463
SD	0.2748	0.0167	0.0053	0.0126	0.1116	0.0922	0.0077	0.0113

Furthermore, the average and normalized importance of each predictor based on the sensitivity analysis (see Table 10) and values of importance (0–1) and performance (1–100) [219] based on the PLS-IPMA (See Table 10 and Appendix B) shows that SCA (AVI = 0.516, NMI = 90.2%, IMP = 0.351 and PFM = 80.89) predicts ATT less than PPN. Similarly, PPN predicts SCA more than ATT, which predicts PPN less than SCA. Although ATT is ranked 3rd among the three predictors of IUSR according to both ANN (NMI = 76.4%) and PLS-IPMA (IMP = 0.293 and PFM = 78.95), SCA is the most important predictor of IUSR according to ANN whereas PPN is the most important predictor of IUSR according to PLS-IPMA. However, although the demographic effects (individual's types of social media use, gender, and usage rate) have some importance (i.e., average importance: 0.036, 0.033, 0.078; normalized importance % :12, 11, 26), their inclusion in the ANN analysis had no significant effect on the rank of the main variables in terms of importance or performance in the model as it was found in the PLS-SEM and CB-SEM results.

Table 10. Sensitivity analysis: Importance, performance, and ranks of the predictors.

ANN Analysis														PLS Analysis Rank	
Relative Importance											AVI	NMI	IMP	PFM	ANN/PLS
ANN	1	2	3	4	5	6	7	8	9	10					
Model 1															
SCA→ATT	0.435	0.497	0.323	0.927	0.547	0.541	0.489	0.44	0.483	0.479	0.516	90.2%	0.351	80.89	2
PPN→ATT	0.565	0.503	0.677	0.073	0.453	0.459	0.511	0.560	0.517	0.521	0.484	100.0%	0.0359	82.73	1
Model 2															
ATT→SCA	0.297	0.258	0.295	0.292	0.333	0.42	0.306	0.352	0.495	0.223	0.3271	50.7%	0.316	78.98	2
PPN→SCA	0.703	0.742	0.705	0.708	0.667	0.58	0.694	0.648	0.505	0.777	0.6729	100.0%	0.447	82.68	1
Model 3															
ATT→PPN	0.451	0.547	0.481	0.459	0.488	0.483	0.487	0.495	0.493	0.48	0.4864	83.9%	0.324	78.94	2
SCA→PPN	0.549	0.453	0.519	0.541	0.512	0.517	0.513	0.505	0.507	0.52	0.5136	100.0%	0.443	80.87	1
Model 4 (combined model)															
ATT→IUSR	0.345	0.302	0.191	0.301	0.290	0.346	0.320	0.244	0.283	0.283	0.291	76.4%	0.293	78.95	3
SCA→IUSR	0.375	0.419	0.418	0.405	0.364	0.334	0.376	0.470	0.264	0.427	0.385	100.0%	0.333	80.88	1/2
PPN→IUSR	0.280	0.279	0.392	0.294	0.346	0.319	0.304	0.286	0.454	0.290	0.324	84.3%	0.335	82.71	2/1
Model 5. Demographic variables with the main variables															
MUSM											0.036	12.2			5
GEN											0.033	11.1			6
USG											0.078	26.4			4
ATT											0.272	91.0			3
PPN											0.278	92.8			2
SCA											0.300	100			1

Note. AVI = Average importance. NMI = Normalized importance. IMP = importance, and PFM = performance based on PLSpredict.

4. Discussion

This study made a significant attempt in social media discipline to explain individuals' "intention" for responsible use of social media by exploring theoretical and empirical interrelationships between attitude and the two under-researched antecedents of behavioral intention, including self-control ability and perceived prosocial norms. Notably, it was involved in rigorous quantitative analysis from scale development to model testing, including CVI, EFA, CFA, PLS-SEM, CB-SEM, ANN, and IPMA analysis. As the study borrowed measurement items from different previous studies instead of a single study due to the unavailability of abstract scales in social media literature to measure ASP, firstly, it conducted a face validity to ensure the items' ability to reflect on what they were intended to measure [144,147,149]. Second, it rigorously checked the relevance and necessity of the items using CVI, CVR, and KAPPA tests using the scores given by a panel of experts for each item in the study [150,151].

As the current study modified the original TPB a little by adding two under-researched variables (i.e., SCA and PPN) to the two established components of TPB (i.e., ATT, intention), so for the validity of such theoretical development and predictability of the variables, PLS-SEM was used as recommended by the experts [211]. However, some researchers still think that PLS-SEM is only suitable for an exploratory study, and the standard PLS algorithm provides inconsistent results, so instead of standard PLS, a consistent partial least square (PLSc-SEM) approach was applied in analyzing the data [142,143,213]. Moreover, as the authors wanted to test an established theory and conclude the findings in the current context (i.e., confirmation), the CB-SEM was used to analyze the data [140,141,145–148]. However, in a technical sense, both CB-SEM and PLS-SEM are complementary methods, not competitive with each other [175,176,211].

In addition to conducting the abovementioned tests, for the robustness check of the model's fitness, the present study conducted the PLSpredict test [175,216]. Furthermore, as a part of the two-stage hybrid analytical procedure, artificial neural network analysis (ANN) was carried out to prioritize and rank the antecedents [190,192] of IUSR. Supplementing SEM with a neural network-based analysis addressed the issues related to non-linearity, sample size (i.e., ANN predicts better even for $100 < n < 500$), predictive accuracy, and non-normality of data [190,191,204]. Also, recently ANN is increasingly being used by researchers studying social media users' behavior [190,192,216]. Therefore, the study's insights generated through a rigorous process have theoretical and practical implications for developing measures to motivate young people to be more responsible on social media.

The current study used convenience sampling due to its advantages over other sampling techniques in the current context. First, convenience sampling dominates social science research, and undergraduate students dominate social media platforms in terms of usage or engagement [38–41,220–223]. They are the widely used source of convenience samples [223–225]. Second, the effects of the different sources of a convenience sample, either student, crowdsourced, professional panel, or respondent-driven social network, do not differ a much [224,225]. Third, many studies around the world used university student social media users as a convenient sample [221,226,227]. Most of them recruited respondents conveniently within the researchers' networks by sending invitations to the participants via email, Messenger (Facebook), WhatsApp, or the researcher's own public social media page [38,41,221,226,227]. Fourth, the study considered a few context-specific factors [221,222]. Fifth, as the social media population is vast [228], without having a population sampling frame (the exact number/statistics), the use of random sampling or any probability sampling techniques could target the wrong sample [221,222,227,228]. Sixth, it was beyond the capacity of the graduate researcher with limited resources, time, and effort/workforce to higher participants based on outsourcing [228,229]. Finally, although there was a chance of selection bias/social desirability or common method bias, the satisfactory results of Harman's single-factor analysis [195], latent variable correlation matrix [196], variance inflationary factor-VIF [189], and the marker variable test addressed the issue [197,198]. Thus, the study had no drawbacks using a convenience sample as it modeled the relationships between a set of variables producing statistically significant parameter estimates, according to the researchers [230,231].

The primary concern of the current study was to measure “intention” for responsible use of social media irrespective of the types of social media more abused or more prosocially used by the users. However, there are different social media platforms with different functions and capabilities. For example, private messaging applications such as WhatsApp, Snapchat, and Facebook Messenger, are mainly used by people for sharing political issues and news, accessing information, and communicating with businesses than for casual/informal communication [232]. Some people find YouTube, WhatsApp, Facebook, and Instagram [233,234] or TikTok [233] as learning media or knowledge acquisition platforms [233–235]. Although people can share misinformation both on Facebook and WhatsApp, social corrections are more likely to be experienced by users or expressed on WhatsApp than on Facebook due to its end-to-end encryption facilities [232]. Similarly, YouTube has deeply influenced users’ perception of its useability as a knowledge acquisition platform, complementary tool in the academic world, or non-educational or entertainment platform [233,235].

In contrast, TikTok is perceived as a socialization and self-expression platform due to the types of uploaded content and limited time allowed for the content [233]. Many social media users still believe that no one social platform is free from sextortion, sexting, revenge porn, bullying, catfishing, and scamming [25]. So, concluding that a particular social media is created only for good deeds, or one is more effective or more misused than the others, may lead to a meaningless debate [232–234,236–238]. Therefore, looking beyond the differences between social media, the current study took a broader view of it and contextualized its responsible use, which may apply to all social media irrespective of their types. This assumption is supported by the results of PLS-SEM and ANN analysis. The results show that the use of different types of social media by the users has no differential effects (only 0.036) compared to the effects of ATT (0.272), SCA (0.278), and PPN (0.300) on IUSR in the model.

Based on these circumstances, it is less important to think about how much a particular social media is being abused than the others due to different features and facilities or security measures they offer [239,240]. In general, it is now more essential to think about abuse or irresponsible use and prosocial and responsible use of social media by its users, as any abuse may create severe threats to the victims based on their situations [21,23]. For example, the consequences of a person’s addiction to any social media may range from a myriad of mental health conditions to a severe psychological disorder or various kinds of disruptions/interferences in real life, irrespective of the type of social media that person use [238]. Thus, it is more critical to reduce abuse to protect young generations before they become obsessed [85,86].

Similarly, any prosocial use of social media, for example, a simple social action of a bystander (i.e., helping others in the digital communities) [100,120], may contribute to minimizing cyber victimization [100,120]. Alternatively, a small donation can stimulate more and more charities [241–244]. Therefore, promoting prosocial behavior and discouraging all forms of abuse through psychosocial means are essential [7,48,49]. However, it is a real challenge to minimize social media abuse (i.e., rumors or misinformation goes viral in a minute) or their consequences immediately, either by the media authority or legal prosecution body, before they damage society [222,239,240,245]. Hence, researchers were less engaged in praising or criticizing a particular social media platform and more in exploring the psychosocial factors of individual content creators or consumers on social media [235]. In addition, they explored ways to increase awareness, consensus, and proactive efforts among stakeholders to establish preventive and intervention initiatives in addressing various social concerns as the digital era continues evolving [25,246].

In contrast, prosocial actions may have conspicuous values, or prosocial users may have a desire for intangible recognition (e.g., a 'Thank you post on Facebook or a gold star icon') [244], or they may want to attain a warm glow or satisfy social network enhancement needs [182]. Such a reputational motivation for prosocial behavior, although a little criticized due to blatant benevolence [182], instead of reducing prosociality, may trigger prosocial actions by providing a more precise signal of altruism to others [182,244]. This help counterbalances online anti-social behaviors [182]. It is due to the fact that cultivating prosociality requires the efforts of family, friends, organizations, networks, schools, or members of the broader society [244]. An online youth's prosocial behavior triggers more prosocial behavior than in-person as young people are motivated to engage in prosociality by observing their peers' online behaviors and receiving online feedback [247–249].

4.1. General Discussion of the Findings

The current study finds that ATT to the responsible use of social media can significantly predict social media users' IUSR. In the past, ATT predicted disgusting video sharing online [241] or intention to involve in cyberbullying perpetration [102]. So, the direct relationship between ATT and intention claims their stronger position in the proposed model. Although ATT has the least predictive power compared to SCA and PPN (36%), it is explained substantially (53%) by SCA and PPN in the model, according to the experts' suggested criteria [189,210].

This study finds that SCA significantly predicts IUSR. In the past, it was found that SCA restrained impulsivity and predicted Facebook addiction [124]. Those with higher SCA consume less time on Facebook and have a smaller number of posts, but low SCA significantly associates cyberbullying perpetration [90]. Moreover, the present investigation finds that PPN can substantially influence social media users' IUSR with greater predictability and explanatory power than ATT in the proposed model. This result is similar to a few past studies, which explored that PPN based on participating in an extracurricular program triggered friends' support for academic activities [242]. Also, it was found that prosocial cultural norms and online social support jointly stimulated donation behavior [243], and PPN minimized social risks of peer interactions and reduced anti-bullying interventions among the youth [77].

While investigating the correlation or causal relationships and mediators among ASP, the current findings are similar to the results of some previous studies while contradicting others. A study by Curtis et al. [65] claimed that ATT and SCA positively correlated. However, both were negatively associated with students' intention to plagiarize (unethical behavior) [65], which is similar to the current study as ATT and SCA are found positively related to IUSR (ethical behavior). Although Cao and Li [80] agreed that ATT and SCA correlate toward COVID-19 vaccination intention, the exertion of SCA decreased people's intention to get a COVID-19 vaccine. As a tiny percentage of variance in "intention" was explained by SCA in their model, they doubted that their model might miss other predictors.

In contrast, the current study finds that a unit change in a person's SCA will lead to a 36% change in behavioral intention in a composite model, whereas it alone can explain a 65% variance in intention compared to ATT (60%) and PPN (64%) that limits the chance of including a few more variables in the model. Therefore, the current study aligns with other studies [189,210,250] that found that self-control ability, not self-control failure, predicts intention to reduce social media addictive behavior [64]. Thus, it can be assumed that SCA [148] has not adequately been reflected in the items to measure intention for COVID-19 vaccination in Cao and Li's study [69].

The current study finds that ATT and PPN are strongly correlated. Also, higher levels of prosocial behavior among classmates predicted negative attitudes toward future antisocial behavior in a past study [109], which is in line with the current study. Also, the present study shows that ATT partially mediates the relationship between PPN and

IUSR, whereas, in the past, it was found that classmates' PPN was not mediated by an individual's ATT toward antisocial behavior [109]. The current study reflected both the inhibition of antisocial behavioral aspects and promotion of prosocial behavioral aspects in the items to measure the constructs as suggested by some researchers [251], who showed that attachments to prosocial peers directly influence ATT, and ATT mediates the relations between peer norms and prosocial behaviors in a longitudinal study. However, it was unclear whether ATT fully or partially mediates the relationship between PPN and intention in that model. There is also evidence in the literature that ATT mediates the relations between antisocial norms (civil negativity) and prosocial behavior [97].

Although previous studies found that a favorable ATT mediates the relationship between SCA and intention to academic dishonesty [125,252] or other deviant behavior [221], the current findings show that ATT has not mediated the relationship between SCA and IUSR at α = 5% (95% CI: p = 0.062) but may mediate at α =10% (which is not widely practiced). As with the current results, [217] it was found in the past that PPN directly and significantly impacted behavior, whereas ATT could not mediate the relation between PPN and prosocial behavior [217]. In the current context, ATT has less predictive power than SCA or PPN in the model (i.e., 36% compared to 43% or 42%). The reason is that there is a gap between ATT and intention in predicting responsible behavior, as was found while predicting green or sustainable consumption behavior [58,60]. Also, another reason is that when SCA is high, ATT may not be a significant intervener in behavioral intention. For example, it was found in the case of predicting social media users' cyberbullying perpetration [112] or Facebook addiction behavior [124].

In the current study, SCA neither mediates the relationship between PPN and IUSR nor the relationship between ATT and IUSR at α =5% (95% CI; p = 0.052 and 0.055 respectively) but may mediate at α =10% (which is not widely practiced). The current study also finds that SCA and PPN are strongly correlated and can influence each other, as was previously noticed in predicting prosocial or voluntary employee behavior in an organization [218]. Also, such a situation was noticed in predicting prosocial behavior in an anonymous economic dictator game [81]. In contrast, PPN mediates the relationships between SCA and social media users' IUSR, as a previous study on soccer players [105] found that social learning mediated the relationship between personal control and antisocial behavior. The strong relationship between SCA and PPN in the current context explains that individuals possessing a remarkable ability to think before acting and follow a plan on the stated norms facilitate more normative behaviors [129,130]. For example, it was found that self-regulatory ability was positively associated with prosocial behaviors during COVID-19 [129]. Therefore, SCA and PPN should be promoted among all social media users, specifically those accompanied by good or prosocial friendships, to motivate more prosocial behaviors among social media users [130].

Furthermore, the relationships between the variables in terms of the results of artificial neural network analysis are also supported by previous studies conducted in the responsible behavior context. However, the results of a previous study (e.g., misinformation sharing and social media fatigue study) based on ANN and PLS-SEM analysis contradict the current findings. In that study, the average importance (ANN = 0.02–0.40 and PLS-SEM = −0.00–0.48) of the antecedents was very inconsistent, whereas, in the current study, the importance of ATT, SCA, and PPN are very consistent (ANN = 0.29–0.38 and PLS-SEM = 0.293–0.335). Thus, the results of ANN analysis also prove the substantial importance and predictive accuracy of SCA and PPN along with ATT in the TPB framework. Therefore, the proposed model may be applicable in different contexts.

4.2. Theoretical Implications

The current study aimed to explore whether and how ASP successfully predicts social media users' IUSR in a single framework. It contributes to researching "individuals' social media behavior" with a modified TPB. The findings of this study provide strong corroboration for the applicability of the modified TPB and contribute to new theoretical insights into the under-researched antecedents that may induce young people's IUSR.

First, the primary concern of the current study is social media users' responsibility, which has recently gotten attention and been explained conceptually by a few academics [6,7,10]. However, the present study extended the explanations by measuring social media users' intention to use social media responsibly. While applying TPB in this respect, the current study noted poor predictability of ATT along with PBC and subjective norms on intention [50,58–60,83]. Therefore, the current study wanted to improve ATT's predictability by incorporating SCA and PPN with it, as suggested previously [10,64,72,73]. In the current context, ATT's importance and performance scores are close to the model's SCA and PPN's scores (i.e., 76.4% according to ANN and 78.95/100 according to IPMA) (see Table 10).

Moreover, the present study assumed that social media could only be used responsibly by avoiding the choices of criminal activities and increasing the footprints of prosocial activities. Therefore, it incorporated SCA, which originated as a theory of crime [70,71]. SCA significantly differs from PBC [45,46] and is negatively associated with antisocial or unethical behavior [69] but positively associated with responsible/sustainable behavior [64,72,73]. The importance and performance score of SCA are 0.333 and 80.88/100, respectively, based on PLS-IPMA, placing it as the second most important predictor, whereas according to the ANN, its importance score is 100/100, ranking it as the first among the three predictors of intention.

Furthermore, the study was concerned only with responsible behavior. As subjective norms are stimulated both by good and bad social ties, which can create a gap between ethical norms and ethical behavioral intention [61,62,74,75], the present study assumed that PPN might trigger only prosocial behavioral intention by suppressing antisocial stimuli [59,77,88]. According to the results of PLS-IPMA, PPN is ranked first, whereas it is ranked second according to the results of ANN analysis. So, ATT, SCA, and PPN all have high predictive power as an antecedent to intention in the proposed model [176,189,213].

Second, as PLS-SEM, CB-SEM, and ANN analysis provided very similar results, the addition of the SCA and PPN to ATT in the original TPB framework distinctively increased the predictive power of the variables and explanatory power in behavioral intention (i.e., together explained over 81% of the variance in IUSR) than previously found in many intention-behavior studies [61,62,64,67,68,72–75,176,189,213]. It also demonstrates the scalability and versatility of SCA and PPN, indicating their applicability as a helpful and common foundation for future studies on predicting individuals' social media behavior. Currently explored interrelationships among ATT, SCA, and PPN, and the relationships between ATT-IUSR, SCA-IUSR, and PPN-IUSR, and ATT as a mediator between PPN and IUSR, and PPN as a mediator between SCA and IUSR were consistent with the findings of previous studies conducted in different disciplines [65,78,80,126,129,130,134,241–243]. Therefore, the present study not only predicts the young generation's IUSR but also extends the current understanding of individuals' socially responsible behavior. Therefore, as TPB's [48,49,101] interaction with information and communication or information technology adaptation theories are growing [49,50,72], the proposed modified TPB with ATT, SCA, and PPN as the antecedent to "intention" may be useable in predicting individual's responsible behavior in different contexts.

More importantly, the items used in the current study to measure ATT, SCA, PPN, and IUSR are theoretically related to several interdependent concepts of social sustainability [27–37], which are still under-researched in the social media landscape [32,33,35–37]. For example, the current study may theoretically relate to the "individuals' and communities' well-being" (i.e., authentic self-expression, prosociality, reducing anxiousness but enhancing satisfaction, happiness, or physical, mental, or emotional health: free from being abused or harassed) [32,35]. The following items measured in the study are related to "individuals' and communities' well-being: i) I like to present myself online as someone making positive choices; ii) my favorite online spaces include where people can be respectful to each other; iii) I intensely feel what others feel in good deeds; iv) I can guarantee that I will always justify before posting/sharing/commenting on any photos/videos/texts so that it does not go in the wrong way or embarrass others; v) I immediately sense my friends' discomfort online, even they do not directly communicate with me; and vi) I will console and support those victimized or who experienced any hardship online. Similarly, other items measured in the study are related to a few other social sustainability pillars [27,28,30,33,36].

The current study's findings afforded a substantial theoretical basis for studying the inhibition of antisocial behavior and promotion of prosocial behavior. Thus, this study provides a significant theoretical contribution by explaining and predicting the antecedents and behavioral intention in the modified TPB in the field of social media. Overall, all of the research procedures followed in this study may significantly contribute to existing theoretical and empirical approaches in media and communication studies to be followed by fellow researchers.

4.3. Practical Implications

The study collected data from university student social media users. They are heavy social media users in Bangladesh. Although this sample is perceived as the critical generation for the nation's development, it was previously found to be the most addicted and problematic social media users [24,36,42]. So, the findings of the current study are vital as recently, more antisocial use but less prosocial use of social media by this cohort of social media users have been creating severe threats to social sustainability in Bangladesh and other parts of the world [21,23,38,39,90]. Thus, the current findings may contribute to developing interventions to change social media users' ASP to shape their social media behavior. By explaining a new set of antecedents of IUSR, the current study provides practical implications for the information communication-related stakeholders concerning effective ways to influence social media users' responsible behavior and promote more responsible usage by the young population, who are the prime users of it.

PPN is the strongest direct influencer of IUSR. Thus, this study is justified by using a prosocial dimension in social media use. The government and non-governmental organizations, universities, civil society, and independent stakeholders or online activists must pay greater attention to fostering PPN on social media. Moreover, there is a need to highlight that exercising sufficient SCA is socially desirable behavior and a moral obligation to individuals against antisocial or impulsivity online to enhance users' perception of using social media only for social sustainability. As ATT and SCA positively and directly influence ethical behavior, efforts should be made to enhance young people's favorable evaluation of right or wrong actions on social media.

It is crucial to increase the perceived level of social pressure to develop higher levels of PPN to promote more responsible behavior directly online. However, to activate PPN, it is vital to educate people about the consequences of all of their activities, including how their prosocial behaviors can solve many current societal problems. By exhibiting prosocial sentiments (e.g., praise or helpfulness) and reducing antisocial sentiments (e.g., personal abuse) on social media, PPN can be reinforced to prevent antisocial posts from disrupting people online [202]. All of the discussed measures may capitalize on the roles of ATT and SCA and enhance prosocial use but inhibit antisocial use of social media.

More importantly, for example, social media users may practice the following as measured in the current study: i) present themselves authentically and positively; ii) respect each other online; iii) resist their temptations, and avoid unexpected things/sharing or adding arguments to rumors or partial news; iv) intensely support the good deeds; v) give mental and social support to the victims; vi) guide friends on more efficient/acceptable use of social media; vii) justify the consequences of every action before completing; and viii) engage with more creative learning/sharing or eco-prosumption purposes. If social media users do these activities as mentioned, a shared meaning among the social media communities may be created, whereas safety and security, impartiality, integrity, trustworthiness, equality, health, communal stability, social capital, and social cohesion may be enhanced. If social media users avoid addictive use and abuse and instead engage in more prosocial use, everyone may get an environment where they can interact, work and live peacefully, and a primary goal of social sustainability might be achieved [28,30,33].

4.4. Limitations and Direction for Future Study

Although the findings of this study have significant theoretical and practical implications, a few possible limitations of the present study may derive some avenues for future research. At first, as the current study mainly concerned testing the hypothetical model with the main variables, the effect of demographic properties were controlled. However, as there was variability (although not significant) in the frequency of use of social media users, types of social media use, and gender of the social media users, individual differences might be a matter. Therefore, in the future, a mean comparison test, for example, ANOVA (Levene's test for equality of variances, post hoc test with Bonferroni, can be carried out to see how much the individual differences matter. However, the current study has checked the effects of the demographic variables in the model using both SEM and ANN analysis and found that although they have some degrees of importance, their inclusion has not affected the rank of ATT, SCA, or PPN in the model.

As the current set of antecedents explained over 81% variance in IUSR, it might be assumed that not many other factors are potentially omitted in the model. However, a few variables might be added to the proposed model as a moderator between the antecedents and IUSR and might be tested in a different context to see how they improve the model's explanatory power. First, "Glocal social media literacy" considers both social media skills that are transversal across different social media (global) and that pertain to a specific social media platform (local) [253]. It may enhance search efficiency, protection, communication, collaboration, creation, and problem-solving, and may determine the scope of a person on social media (what they should and should not do). Thus, it may minimize social media misuse [253,254]. So, it may be a moderator between self-control ability and IUSR. Also, "intensive gratification needs" may create high-quality relationships, enhance the sense of meaningful connectedness, and demonstrate genuine care. It also increases common sense, concern, and positive emotions through appropriate comments or a spiral of positive exchanges that lead to social integration and identity [255]. So, it may be a moderator between prosocial norms and intention to use social media responsibly [255]. Finally, "moral/ethical perfectionism" is related to moral judgments and moral values derived from perfectionism, which sets exceptionally high standards of perfect behavior over personal mistakes and self-correction based on others' negative evaluations [249]. Thus, it may be a moderator between SCA, PPN, and IUSR [191,204,255]. Additional demographic variables might be tested in the future while sampling participants from a larger population instead of only a student cohort of social media users to see how much their impact can be controlled. Also, the target construct (i.e., IUSR) may include more items relevant to social responsibilities on social media to test how the antecedents affect IUSR or how people choose between different responsibilities.

The present study is based only on the current university student social media user population, whereas everyone in society can irresponsibly use social media. So, in the future, a hybrid survey combining an online survey with a mass household survey of diversified groups from the country's adult population can be conducted to ensure more representativeness of the data and generalizability. Also, researchers may carry out a cross-cultural investigation to generalize the findings. The current survey was based on a self-administered questionnaire, so the participants might have over-reported their choices due to social desirability (although the results of several common method variance tests were satisfactory). Therefore, in the future, researchers may conduct a longitudinal study. Also, practitioners or academics can conduct any promotional or communicational intervention-based experiment or even do a sentiment analysis/user-generated content analysis using neural network technologies to understand the social media users' intentions and actual behavior [256,257]. As the current study is part of a graduate research project, the next phase will explore how to influence social media users' ASP and actual behavior on social media.

5. Conclusions

Nowadays, misuse or abuse of social media has become a commonplace and a major global social issue, which attracts the immediate attention of academia to research individuals' responsible social media behavior. However, very few studies have addressed the psychosocial antecedents to an individual's responsible behavior on social media. Therefore, the current study aimed to explain social media users' IUSR by applying the TPB model. Two concepts (SCA and PPN) popular in antisocial/criminal and prosocial behavioral studies but under-researched in the social media study were added to ATT and "intention" to test how strongly they predict IUSR towards proposing a modified TPB. A pool of items was generated by reviewing relevant literature from multiple disciplines. Then five information system graduates checked the items' clarity, understandability, and representativeness before sending them to a panel of experts for a content validity test. The selected items were pretested, and the final questionnaire was developed using a Google Form. Then, an online survey was conducted among current university student social media users in Bangladesh.

The similar results generated by PLSc-SEM and CB-SEM for reliability, convergent validity, discriminant validity, path coefficients, and model fit indices are supported by the contemporary experts' suggested criteria and previous studies' findings. Also, PLS and ANN analysis generated similar outcomes in terms of predictability of the antecedents. Attitudes, self-control ability, and prosocial norms (ASP) directly and significantly impacted intention and were strongly correlated and influenced each other. However, ATT partially mediated the relationship between PPN and IUSR, and PPN partially mediated the relationship between SCA and IUSR. SCA and PPN had a greater explanatory and predictability power than ATT in the model. However, as the relationships between PPN and ATT or ATT and SCA were less researched, particularly in the social media context, their inclusion gave a novelty to the existing TPB model. So, the modified TPB model may effectively predict Bangladeshi social media users' IUSR. Moreover, as the findings indicated that the items used in the current model perfectly reflect their theoretical domains or concepts, the antecedents might also be used to measure social media users' IUSR in different contexts.

The outcome of this study not only may enhance our understanding of the sociological and psychological factors of social media users' behavioral intention but also provide some keys to the relevant stakeholders to implement various measures to motivate more responsible use of social media towards social sustainability.

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Informed Consent Statement: Informed consent, attached to the survey form, was obtained from all of the participants online.

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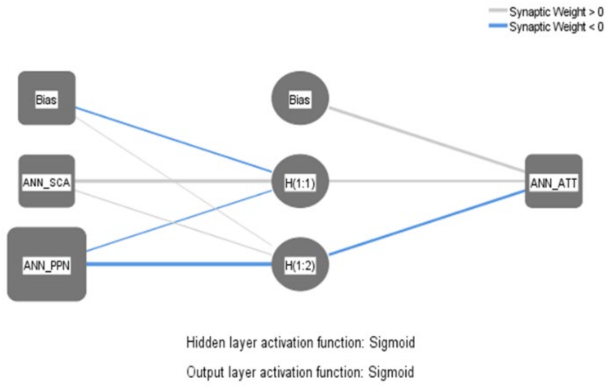
Appendix A

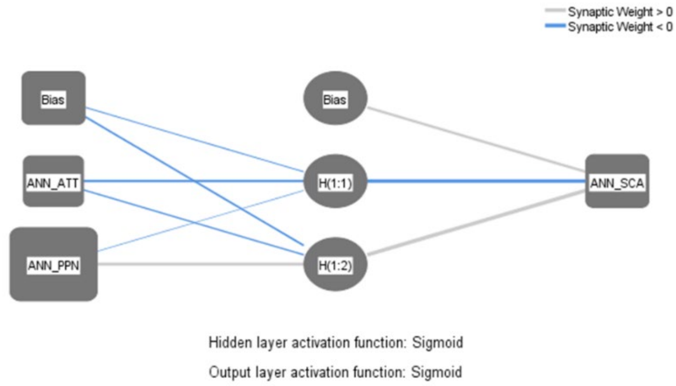
Table A1. Linearity Test: ANOVA.

DV * IV	Between Groups	Sum of Squares	df	Mean Square	F	Sig.
ATT * SCA	(Combined)	74.617	17	4.389	11.332	0.000
	Linearity	50.780	1	50.780	131.099	0.000
	Deviation from Linearity	23.836	16	1.490	3.846	0.000
ATT * PPN	(Combined)	75.974	15	5.065	13.428	0.000
	Linearity	51.365	1	51.365	136.177	0.000
	Deviation from Linearity	24.609	14	1.758	4.660	0.000
SCA * ATT	(Combined)	82.753	11	7.523	12.438	0.000
	Linearity	69.433	1	69.433	114.798	0.000
	Deviation from Linearity	13.320	10	1.332	2.202	0.019
SCA * PPN	(Combined)	107.432	15	7.162	14.358	0.000
	Linearity	83.257	1	83.257	166.902	0.000
	Deviation from Linearity	24.175	14	1.727	3.462	0.000
PPN * ATT	(Combined)	71.782	11	6.526	10.727	0.000
	Linearity	66.850	1	66.850	109.888	0.000
	Deviation from Linearity	4.932	10	0.493	0.811	0.619
PPN * SCA	(Combined)	114.120	17	6.713	15.894	0.000
	Linearity	79.247	1	79.247	187.635	0.000
	Deviation from Linearity	34.873	16	2.180	5.161	0.000
IUSR * ATT	(Combined)	86.182	11	7.835	19.335	0.000
	Linearity	78.514	1	78.514	193.760	0.000
	Deviation from Linearity	7.669	10	0.767	1.893	0.048
IUSR * SCA	(Combined)	119.036	17	7.002	27.040	0.000
	Linearity	87.136	1	87.136	336.496	0.000
	Deviation from Linearity	31.900	16	1.994	7.699	0.000
IUSR * PPN	(Combined)	113.539	15	7.569	26.779	0.000
	Linearity	87.128	1	87.128	308.243	0.000
	Deviation from Linearity	26.411	14	1.886	6.674	0.000

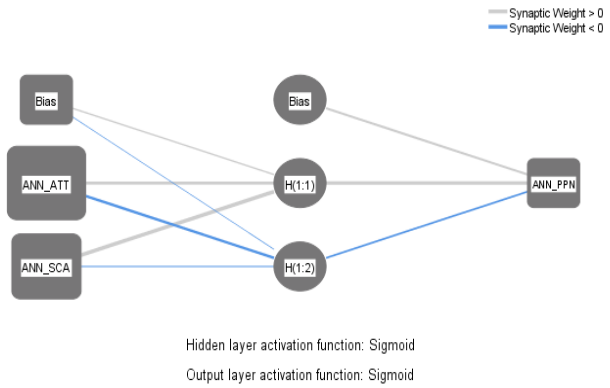
Appendix B



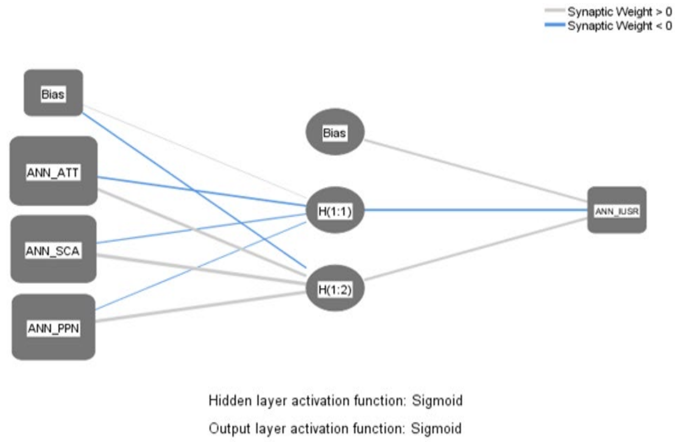
ANN Model B1



ANN Model B2.



ANN Model B3



ANN Model B4 (combined model)

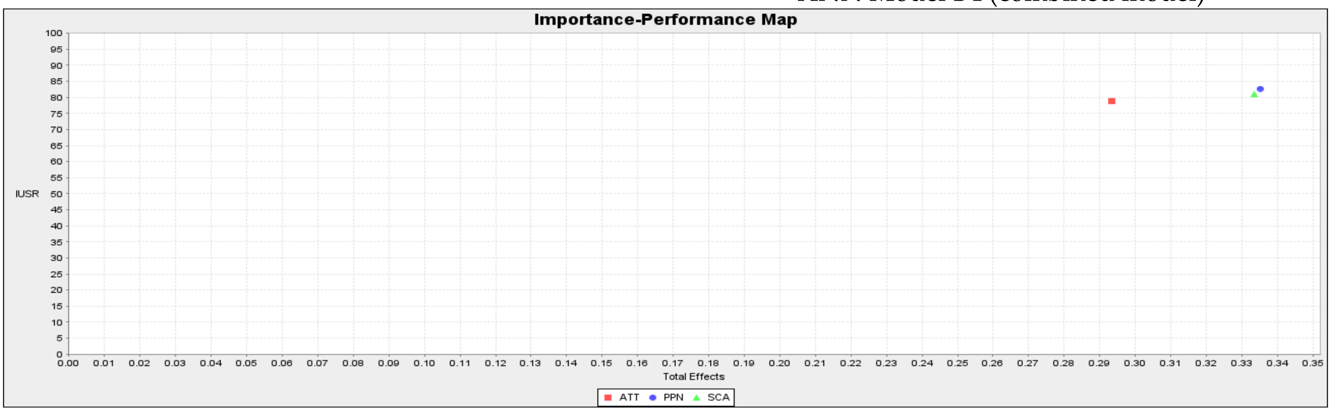


Figure A1. IPMA. Note: In this two-dimensional graph, the horizontal axis describes the "importance" (total effect) of predictors using a scale from 0 to 1, and the vertical axis describes their performance using a scale from 0 to 100. ATT, SCA, and PPN are presented in different colors.

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