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Why Following Friends Can Hurt You: A Replication Study

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Abstract:

This study is a methodological replication of the work originally published in Information Systems Research by Krasnova et al. (2015). The original work studied the effects of envy in the context of Social Network Sites (SNSs) among college-age users. We adapt the constructs and measurement items of the original survey but change the context of the SNS to Instagram instead of Facebook. We also target a sample of college-age students from the United States instead of from Germany. The results of our replication support six of the seven hypotheses from the original paper. Confirming these results reinforce the model proposed by Krasnova et al. (2015). However, our replication did not find a strong mediation effect from envy on an SNS between the intensity of social information consumption on an SNS and users' cognitive well-being. The results suggest that the difference in population, SNS, or time has led to a change in this effect, inviting further replications and new studies.

Keywords: Envy, self-enhancement, social comparison theory, social media, social networking sites, subjective well-being

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1 Introduction

Social networking sites (SNSs) have seen a tremendous rise in recent years. Since 2010, Americans that actively use at least one SNS have risen from 43% to 72% (Pew Research, 2021a). SNSs allow a level of information sharing and social connection that was before impossible. These connections have been linked to improved cognitive well-being (CWB) in lonely individuals who self-disclose their feelings on an SNS (Lee et al., 2013). However, subsequent studies have found that CWB can be negatively impacted by social comparison (Steers et al., 2014), time spent on an SNS (Huang, 2017), and envy (Lin et al., 2018; Verduyn et al., 2017). This interesting dichotomy of SNSs has invited more targeted research into the complex processes that can impact an SNS user's CWB (Kross et al., 2021).

To understand the underlying factors of these negative effects, Krasnova et al. (2015) analyzed the effects of envy on SNSs among college-age users. The study found feelings of envy on an SNS can lead to a "self-enhancement envy spiral." This phenomenon details how users are more likely to purchase and enhance themselves on an SNS if they feel envious. This behavior leads to envy in others, creating a cycle of negative emotion when using an SNS. However, this study was conducted with college-age German students about the popular SNS Facebook. In a prior study, Krasnova and Veltri (2011) note that German and United States (U.S.) citizens have different motivations and posting behaviors when interacting with an SNS. For example, German citizens generally have higher levels of privacy concern when posting to an SNS than U.S. citizens (Krasnova et al., 2012). Krasnova et al. (2015) noted that "insights into the nature of negative experiences in the SNS context remain scarce, with studies mainly focusing on privacy when discussing users' intentions to continue using the system." This invites further research into the negative effects of SNS sites in different contexts. Therefore, exploring the role of envy with U.S. SNS users may provide new and exciting insights to the information systems (IS) community.

In this study, we aim to methodologically replicate the original work performed by Krasnova et al. (2015) to contribute to post-adoption SNS literature within the IS community. Krasnova et al. (2015) suggested that their study should be extended to different SNSs to compare against their focal SNS, Facebook. In this work, we explore the role of envy on affective well-being (AWB), CWB, and self-enhancement on the popular SNS, Instagram. Users often approach Instagram and Facebook differently, leading to different behaviors in similar contexts (Masciantonio et al., 2021). Therefore, we aim to provide key insights into the similarities and differences between Facebook and Instagram as they pertain to envy, AWB, CWB, and self-enhancement to the IS knowledge base.

The original study examined the relationships of nine reflective first-order constructs and three single-item constructs in the context of SNS usage. The twelve overall constructs are detailed in Table 1.

Table 1. Construct Descriptions

Name	Description
Affective well-being (AWB)	A measurement of the sadness one feels while using an SNS.
Age	The age in years of the subject.
Cognitive well-being (CWB)	A measurement of an individual's satisfaction with life.
Dispositional envy (DE)	One's general tendency to feel envy.
Envy on a social network (ENV)	Situational envy is modified to capture the context of an SNS.
Extraversion (Extra)	The degree to which someone is outgoing and sociable.
Gender	The gender that someone identifies with.
Neuroticism (Neuro)	The degree to which someone gets nervous or does not handle stress well.
Number of SNS friends	The count of friends, followers, or connections someone has on an SNS.
Self-enhancement (SE)	A measurement of how someone posts positive features on social networks.
Social information consumption (SIC)	How much someone consumes social network site media.
Social information sharing (SIS)	How often someone posts on a social network site.

From these twelve constructs, Krasnova et al. (2015) created a theoretical model and posed seven hypotheses for the relationships of the constructs, which are shown in Table 2 and Figure 1.

Table 2. Research Hypotheses

N	Hypothesis
H_1	The intensity of social information consumption on an SNS is positively associated with envy experienced on an SNS.
H_2	Envy experienced on an SNS is negatively associated with users' cognitive well-being.
H_3	Envy experienced on an SNS is negatively associated with users' affective well-being.
H_4	Envy on an SNS mediates the relationship between the intensity of social information consumption on an SNS and users' cognitive well-being.
H_5	Envy on an SNS mediates the relationship between the intensity of social information consumption on an SNS and users' affective well-being.
H_6	Envy on an SNS is positively associated with users' engagement in personal self-enhancement on an SNS.
H_7	Envy on an SNS mediates the relationship between the intensity of social information consumption and users' engagement in self-enhancement on an SNS.

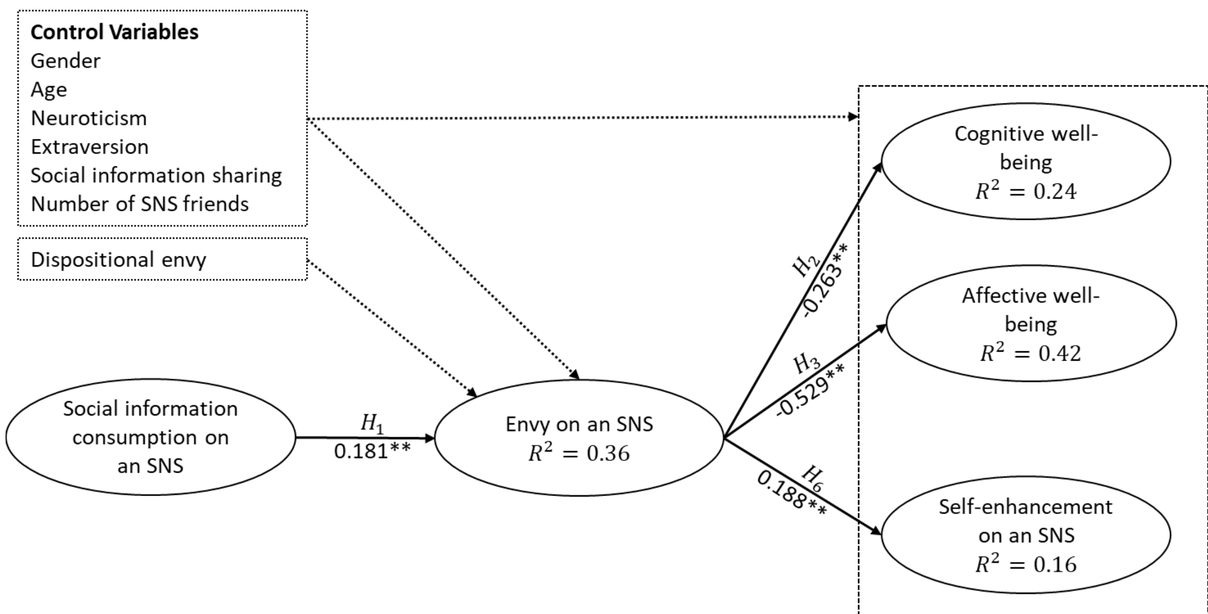

Figure 1. Results of the Original Study Structural Model Analysis (Adapted from Krasnova et al., 2015)

Figure 1 shows the path coefficients, constructs, and results from the original study for the hypotheses that did not explore "Envy on an SNS" as a mediator variable.

2 Method

Following the guidelines of the Transactions in Replication Research journal (Dennis and Valacich, 2015), we conducted a methodological replication of the original work conducted by Krasnova et al. (2015). We note two key changes for our work: First, while the original paper uses Facebook as their SNS, we asked students about the popular SNS, Instagram. This allows us to research another popular SNS that has seen increased behavioral research recently (Sherman et al., 2018; Wong et al., 2019). Second, the original paper uses German college students as a sample, while this study focuses on a large university in the U.S. This allows a comparison between countries and localizes the study to another geopolitical population. Instagram provides an interesting dynamic, as connections can be both one-way and two-way (i.e., one can follow someone, but that person may not follow them back). This contrasts with Facebook, where connections are two-way. Additionally, the primary modality for interactions on Instagram is through images, whereas Facebook posts are a mixture of text and images. However, the age distribution of the two SNSs at the time of each study is similar. Figure 2 shows the age distribution for Instagram in the U.S. in 2021 (Statista, 2022) and Facebook in Germany in 2013 (Statista, 2014).

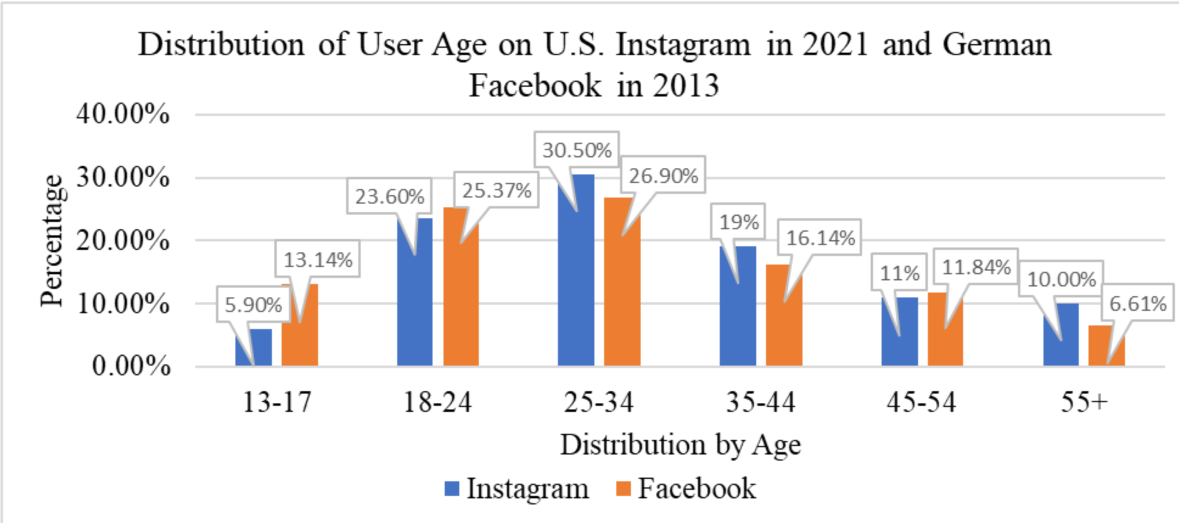

Figure 2. Distribution of User Age on U.S. Instagram in 2021 and German Facebook in 2013

While there are slight differences in age for the two SNSs, each distribution follows a right-skewed bell curve and sees over 50% of users fall within the 18-34 age range. The largest differences are in the 13-17 range (5.90% of Instagram users in 2021 compared to 13.14% of Facebook users in 2013) and the 25-34 range (30.50% of Instagram users in 2021 compared to 26.90% of Facebook users in 2013). However, the median age of the study by Krasnova et al. (2015) and our replication fall in the 18-24 range, which has a similar distribution in both SNS (23.60% of Instagram users in 2021 compared to 25.37% of Facebook users in 2013).

Krasnova et al. (2015) used a two-study design to study the effects of envy in SNSs. Their first study was qualitative and aimed to answer two research questions: “Is envy on an SNS driven by a different set of objects compared to the offline settings? And is it (at least partly) induced by information that is unlikely to be available offline?” The results of the first study found that envy was prevalent in college-age users on Facebook. Additionally, the authors found that envy from an SNS was represented by different terms than envy in an offline setting. This suggested to the authors that envy on an SNS had unique characteristics and terms. The authors used the results of the first study to justify a more in-depth exploration and guide their research questions for their second study. Their second study used a quantitative survey to measure the effects of envy on CWB and AWB and self-enhancement on a SNS. As no meta-inferences were drawn between studies 1 and 2, and study 1 guided the development of study 2, we choose to only replicate study 2 in this work.

In the original study, researchers targeted college-age Facebook users in Germany using a convenience sampling procedure at a large university. The researchers offered a chance to win a €10 Amazon gift card upon successful completion. In our study, we targeted college-age Instagram users in the United States using a convenience sampling procedure at a large university. Our survey uses the same items and constructs as Krasnova et al. (2015) adapted for our Instagram context (shown in Appendix Table A1). Changes to items were kept to a minimum where possible (e.g., changing the term “Facebook” to “Instagram”). Students were guaranteed extra credit in a large, mandatory class for their major upon successful completion. The results of both the original and replication data collections are presented in Table 3.

Table 3. Collection Details		
Variables	**Original**	**Replication**
Country	Germany	United States
Sample Size	-	290
Usable Samples	509	221
Female/Male	66.1%/33.6%	52.04%/47.96%
Age (median)	24	21
Number of SNS Friends/Followers (median)	200	500

From Table 3, we make four key observations. First, our sample size is less than half of the initial study. However, using an a priori sample size calculation (effect size of 0.5, a desired statistical power level of 0.8, probability level of 0.05, 9 latent variables, and 35 observed variables), we determined that the minimum sample size needed is 107. Re-running the a priori sample size calculation with the single-item constructs of age, gender, and social information consumption, our usable samples of 221 is greater than the minimum sample size of 213. Second, the original study had a much greater difference between female and male subjects than our replication. Third, the original study had an older median age than our replication. However, these ages fall within the second most common age bracket for each SNS at the time of data collection, as shown in Figure 2. Fourth, the median number of SNS friends (for the Instagram context, followers) was less than half in the original study than our study (200 vs 500).

3 Results

3.1 Measurement Model Assessment

In the original study and our replication, all constructs are modeled as reflective with the SmartPLS tool (Ringle et al., 2015). Each construct is comprised of survey items that use the Likert scale. Each item uses either a 5-point or 7-point Likert scale. Full details of our survey constructs and items are shown in Appendix A.

Following the original study, we ensure the validity and reliability of our constructs using factor loadings, average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha (CA). The recommended threshold for factor loadings is 0.6. Our analysis of the factor loadings shows that 34 of our 35 items exceed 0.6 with 14 of the items exceeding 0.8 (see Appendix Table B1 for full factor loadings of each item). We then use the results from our factor analysis to calculate AVE, CR, and CA for each multi-item construct, as shown in Table 4.

Table 4. Construct Descriptive Statistics						
	Original			**Replication**		
Construct	**AVE**	**CR**	**CA**	**AVE**	**CR**	**CA**
AWB	0.703	0.922	0.894	0.637	0.887	0.812
CWB	0.754	0.902	0.837	0.684	0.86	0.743
DE	0.68	0.894	0.843	0.599	0.857	0.754
ENV	0.572	0.888	0.848	0.559	0.883	0.703
Extra	0.857	0.923	0.834	0.541	0.702	0.794
Neuro	0.75	0.857	0.666	0.732	0.845	0.825
SE	0.743	0.897	0.828	0.709	0.879	0.774
SIC	0.646	0.88	0.818	0.567	0.839	0.769
SIS	0.736	0.893	0.821	0.574	0.799	0.795

The recommended threshold for AVE is 0.5 to achieve convergent validity (Fornell and Larcker, 1981). In both the original study and our replication, all constructs are 0.5 or greater. To measure the internal consistency of the model, CR, and CA should both be above 0.7 (Nunnally, 1975; Hair et al., 2011). In both the original study and our replication, all constructs are 0.7 or greater for CR and CA (except for Neuro CA at 0.666 in the original study). To assess discriminant validity, we measured the square root of AVE against the inter-construct correlations, shown in Table 5.

Table 5. Square Root of AVE and Correlations Between Latent Variables

	AWB	CWB	DE	ENV	Extra	Neuro	SE	SIC	SIS
AWB	**0.798**								
CWB	0.132	**0.827**							
DE	-0.215	-0.137	**0.774**						
ENV	-0.157	-0.106	0.284	**0.748**					
Extra	0.021	0.154	-0.095	0.008	**0.736**				
Neuro	-0.018	-0.208	0.309	0.287	-0.084	**0.856**			
SE	-0.035	0.021	0.034	0.194	0.082	0.042	**0.842**		
SIC	-0.018	0.054	0.022	0.094	0.102	0.045	0.082	**0.753**	
SIS	-0.031	0.024	0.076	0.076	0.154	0.018	0.016	0.287	**0.757**

From Table 5, no inter-construct correlations exceeded the square root of AVE (bolded diagonals). These results hold consistent with the original work and establish the discriminant validity of our measures.

3.2 Structural Model Assessment

In line with the original study, we calculated the direct and indirect path coefficients between constructs to reject or fail to reject our hypotheses. The software SmartPLS (Ringle et al., 2015) was used, and all multi-item constructs were modeled as reflective. Like the original paper, we used a 5,000-sample bootstrap method to estimate the significance of the path coefficients' direct and indirect effects. Figure 3 summarizes the results of our structural model assessment, and further comparisons are made in Tables 6 and 7. While the original paper only showed H_1, H_2, H_3, H_6, (the non-mediating hypotheses) on a structural model, we choose to display all seven hypotheses in Figure 3 to comprehensively model the full results of our replication.

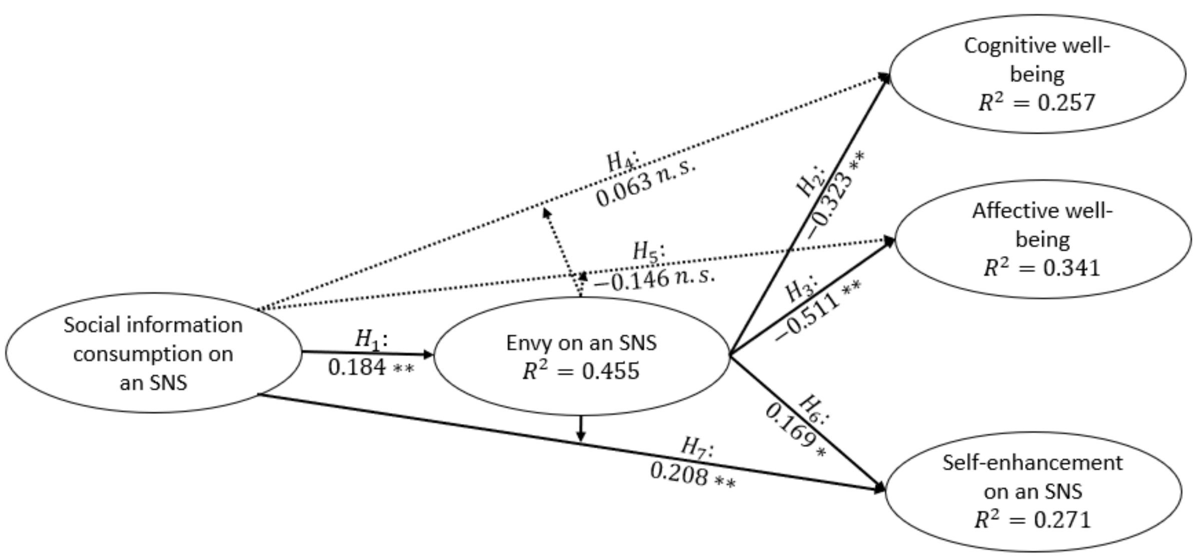

Figure 3. Results of the Replication Study Structural Model Analysis

Table 6. Overview of Direct Findings				
	Original		Replication	
Hypothesis (with direction)	**Path Coefficient**	**Supported?**	**Path Coefficient**	**Supported?**
H_1: SIC → ENV	0.181**	Yes	0.184**	Yes
H_2: ENV → CWB	-0.263**	Yes	-0.323**	Yes
H_3: ENV → AWB	-0.529**	Yes	-0.511**	Yes
H_6: ENV → SE	0.188**	Yes	0.169*	Yes
*: Significant at 5%; **: Significant at 1% or lower				

From Figure 3 and Table 6, we make several observations. First, in terms of explanatory power, our replicated model explains 25.7% percent of our subjects' CWB (against 24% in the original), 34.1% of their AFB (against 42% in the original), and 27.1% of their self-enhancement on an SNS (against 16% in the original model). The results of our control variables (not investigated in the hypotheses) are shown in Appendix C Table C1. These results suggest that other factors can explain the CWB and AWB of students and their tendency towards self-enhancement on an SNS. The results of the direct path coefficients showed a significant positive relationship between social information consumption and envy on an SNS, a significant negative relationship between envy on an SNS and AWB and CWB, and a significant positive effect between envy on an SNS and self-enhancement on an SNS. These results were all consistent with the original study and significant at $p<0.05$.

Table 7. Overview of the Direct and Indirect Effects						
N	**ENV mediates the relationship:**	**Original Indirect Effect**	**Replication Indirect Effect**	**Original Direct Effect**	**Replication Direct Effect**	**Replication Type of Mediation**
H_4	→ CWB	**-0.048****	0.032	0.054	0.063	None
H_5	→ AWB	**-0.096****	**-0.145****	-0.041	-0.146	Full
H_7	→ SE	**0.034****	**0.157****	**0.159****	**0.208****	Partial
*: Significant at 5%; **: Significant at 1% or lower						

From Table 7, we discover a disparity between our replication and the results of the original work. We did not find that envy on an SNS mediates the relationship between the intensity of social information consumption on an SNS and users' CWB. However, the results suggest that envy acts as a mediator between the intensity of social information consumption on an SNS and AWB and engagement in self-enhancement on an SNS.

4 Discussion

To our knowledge, this is the first time a replication has been performed on the original Krasnova et al. (2015) paper. Our methodological replication of the research originally conducted by Krasnova et al. (2015) measured the same constructs and path coefficients as the original work. Additionally, the survey items were kept the same except for changing "Facebook" to "Instagram". Keeping measures and constructs the same allows for a direct comparison between our replicated results and the results of the original work, which are summarized in Table 8.

Table 8. Hypothesis Comparison Between Studies			
N	**Original Study**	**Replication Study**	**Consistent?**

Table 8. Hypothesis Comparison Between Studies			
H_1	Supported	Supported	Yes
H_2	Supported	Supported	Yes
H_3	Supported	Supported	Yes
H_4	Supported	Not Supported	No
H_5	Supported	Supported	Yes
H_6	Supported	Supported	Yes

Despite the difference in collection location (the U.S. instead of Germany) and SNS of focus (Instagram instead of Facebook), our replication found that six of the seven results held. The most interesting result of our replication is that H_4 was not supported. This result implies that the significant negative effect of moderation from social information sharing to CWB that was found in the original work is not present in our replication. We speculate several reasons for this key difference between studies. First, extant literature has discovered that German SNS users allow the use of SNS to negatively influence their subjective well-being (Suphan and Mierzejewska, 2015). However, the same study found that U.S. SNS users did not have this same negative influence on their subjective well-being. Additionally, U.S. students are more likely to use an SNS to socialize and interact with friends (online and in-person) than German students (Suphan and Mierzejewska, 2016). However, this study only focused on the positive effects of SNS usage. These findings may help to explain why U.S. students are less likely to fall into the self-enhancement envy spiral and allow envy to affect their CWB.

Second, the one-way aspect of Instagram may suggest the difference in the mediation of envy on CWB. Instagram is commonly used for upward social comparison whereas Facebook is commonly used for social support (Masciantonio et al., 2021). Instagram users often follow people (who often do not follow them back) who are salient figures within their community (Meier et al., 2020). Envy stemming from upward social comparison to these salient figures on Instagram can be benign and lead to inspiration (Meier and Schäfer, 2018). This inspiration then further led to positive effects on well-being (Meier et al., 2020). Krasnova et al. (2015) did not consider the difference between malicious and benign envy in their original study.

Third, there is an eight-year difference in the two data collections (2021 in our replication, 2013 in the original). The subjects in the original work belong to Gen Y, while our subjects belong to Gen Z. Prior literature suggests that Gen Y social media usage was driven by unfulfilled social needs (e.g., interpersonal support) (Wang et al., 2012). Those unfilled needs may have driven envy and negative effects on CWB. However, Gen Z's social media usage is largely driven by social interactions (Zhao, 2021). Further, the Gen Z users that regulate their social interactions (i.e., are not addicted to them) found improvements in their subjective well-being (Zhao, 2021). However, this study surveyed a population of Chinese college students. Therefore, more research insights may be required in this area of speculation.

We also found several statistically significant differences within control variables (Appendix C) from the original study. First, our replication found that age did not have a significant moderating effect on AWB, while the original paper found a significant positive effect. We consider that both our mean and median age are 21, whereas the original paper had a median age of 24. Further, 93% of our subjects were either 20 or 21. The narrow range of ages in our replication may have led to the insignificant path coefficient between age and AWB. Second, our replication found that the construct of neuroticism did not have a significant moderating effect on CWB, while the original paper found a significant negative effect. Our subjects' average feelings of neuroticism were higher than the original paper, which could have led to this non-significant result.

Overall, these results contribute to the extant literature on SNSs by showing the generalizability of the original research framework.

4.1 Limitations

Our use of convenience sampling with students can cause several limitations. The survey was administered near the end of the semester when students would most likely want extra credit, but also be the busiest. This raises the concern that students may have lied and claimed they had an active Instagram account to be eligible for the extra credit. At the time of data collection, about 71% of Gen Z had an active Instagram account (Pew Research, 2021b). The subjects are explicitly told if they do not answer honestly, they will not receive extra credit. Additionally, we included attention checks in our survey and omit the responses that did not pass the attention checks to potentially reduce this bias.

Another potential limitation is the smaller sample size in comparison to the original work, which could potentially have influenced the overall results. However, as discussed previously, our a priori sample size calculations determined that our sample size was large enough to detect the effects of the original study.

4.2 Next Steps

We have identified several promising next steps for future replications. First, an interesting follow-up study could ask how U.S. students and German students interact with their SNS, and then measure what causes feelings of envy when using an SNS. This extension could reduce the speculation in our different results from the original study and provide key insights into how SNS use intention can affect the well-being of users. Additionally, new and interesting SNSs (e.g., TikTok, Twitter, Reddit) could be explored to further identify interesting usage intentions between the groups.

Second, follow-up studies could explore the difference between benign and malicious envy on well-being. The work by Wu and Srite (2021) provides an excellent starting point for examining how different types of envy (benign and malicious) on SNSs lead to different types of future use intention. Additionally, future work could measure benign and malicious envy based on geopolitical differences (e.g., Chinese vs German vs American).

Third, this replication work can be extended to additional generations of users (e.g., Baby Boomers and Gen X). While these generations did not grow up with social media, 70% of Baby Boomers use Facebook regularly (Statista, 2019), while 76% of Gen X use Facebook regularly (Statista, 2020). These older generations are likely to use an SNS for diversion and entertainment (Sheldon et al., 2021). This contrasts with younger generations (Gen Y, Gen Z) that primarily use an SNS for social maintenance (Wang et al., 2012; Zhao, 2021). Therefore, future literature can explore how this usage difference changes feelings of envy, well-being, and self-enhancement.

Fourth, researchers could create meta-inferences from qualitative and quantitative approaches (not studied in this replication), potentially creating a more complete discussion on the role of envy in the context of SNSs. Extant literature has used targeted interviews, focus groups, and generalized surveys to discover the effects of Snapchat (an image based SNS) on mental health (Dunn and Langlais, 2020). The focus group allowed the subjects to converse with each other and illuminate specific reasons that Snapchat caused feelings of anxiety (e.g., always seeing other locations on a map). These interesting meta-inferences and strategies could be applied to our setting of envy, well-being, and self-enhancement on social media to create interesting new conclusions.

5 Conclusion

This paper methodologically replicated the research on the role of envy in the context of SNSs by Krasnova et al. (2015). While the original research used two studies, only the second study was empirically tested. The original research chose Facebook as the SNS of focus and administered a survey to college-age students in Germany. In contrast, our replication asked the same questions in a survey to college-age students in the United States about the newer SNS, Instagram. Our results were largely consistent with the original study (6 of the 7 hypotheses were consistent). The results of the replication suggest that the theories and results developed in the original paper can be generalized to college students in different geopolitical regions and different SNSs. Given how prevalent SNSs have become among all generations, it is important to continue research into their usage and effects on well-being.

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Appendix A: Survey Items

Table A1. Replication Survey Items

Item	Exact Text	Scale
AWB: In the following, you find a list of feelings people have when using Instagram. When you think about how you feel when using Instagram, to what extent do you feel:		
AWB1	Sad?	Likert, 1-5 (item reversed before evaluating)
AWB2	Blue?	Likert, 1-5 (item reversed before evaluating)
AWB3	Downhearted?	Likert, 1-5 (item reversed before evaluating)
AWB4	Alone?	Likert, 1-5 (item reversed before evaluating)
AWB5	Lonely?	Likert, 1-5 (item reversed before evaluating)
CWB: To what extent do you agree with the following statements?		
CWB1	In most ways, my life is close to my ideal.	Likert, 1-7
CWB2	In most ways, my life is close to my ideal.	Likert, 1-7
CWB3	I am satisfied with my life.	Likert, 1-7
DE: To what extent do you agree with the following statements?		
DE1	I feel envy every day.	Likert, 1-7
DE2	The bitter truth is that I generally feel inferior to others.	Likert, 1-7
DE3	Feelings of envy constantly torment me.	Likert, 1-7
DE4	I am troubled by feelings of inadequacy.	Likert, 1-7
ENV: When using Instagram, how often do you think that:		
ENV1	Most of my Instagram friends have it better than I do.	Likert, 1-7
ENV2	The posts of my Instagram friends get more attention (e.g., “likes”, comments, etc.) than mine.	Likert, 1-7
ENV3	I don’t know why, but I usually seem to feel like an underdog on Instagram	Likert, 1-7
ENV4	It is somewhat annoying to see on Instagram how successful some of my Facebook friends are.	
ENV5	It is somewhat disturbing to see how popular some others are on Instagram.	Likert, 1-7
ENV6	It is somehow disturbing when I see on Instagram how much traveling others can afford.	Likert, 1-7
Extra: I see myself as someone who…		
Extra1	...is reserved.	Likert, 1-7
Extra2	...is outgoing, sociable.	Likert, 1-7 (item reversed before evaluating)
Neuro: I see myself as someone who…		
Neuro1	...is relaxed, handles stress well.	Likert, 1-7 (item reversed before evaluating)
Neuro2	...gets nervous easily.	Likert, 1-7
SE: In my communication on Instagram, I tend to…		
SE1	…post only things showing my best side.	Likert, 1-7
SE2	…share stories/photos showing me as a happy person.	Likert, 1-7
SE3	…show positive feelings when posting something.	Likert, 1-7
SIC: On Instagram, how often do you...		

Table A1. Replication Survey Items		
SIC1	...look through your feed.	Likert, 1-7
SIC2	...follow what your friends are sharing.	Likert, 1-7
SIC3	...click through the content your friends have shared (as photos, videos).	Likert, 1-7
SIC4	...browse the photos your friends shared.	Likert, 1-7
SIS: On Instagram, how often do you...		
SIS1	...react to posts of your friends (e.g., by commenting, “liking” etc.).	Likert, 1-7
SIS2	...post something (e.g., story, photos, links, etc.).	Likert, 1-7
SIS3	...keep your friends updated about yourself.	Likert, 1-7

AWB is measured using five items on a reversed 5-point Likert scale, where 1 is almost never and 5 is always. CWB is measured using three items on a 7-point Likert scale, where 1 is strongly disagree and 7 is strongly agree. DE is measured using three items on a 7-point Likert scale, where 1 is strongly disagree and 7 is strongly agree. ENV is measured using six items on a 7-point Likert scale, where 1 is almost never and 7 is very often. Extraversion (Extra) is measured using two items on a reversed 7-point Likert scale, where 1 is strongly agree and 7 is strongly disagree. Neuroticism (Neuro) is measured using two items on a reversed 7-point Likert scale, where 1 is strongly agree and 7 is strongly disagree. SE is measured using three items on a 7-point Likert scale, where 1 is strongly disagree and 7 is strongly agree. SIC is measured using four items on a 7-point Likert scale, where 1 is never and 7 is several times a day. SIS is measured using three items on a 7-point Likert scale, where 1 is never and 7 is several times a day.

Appendix B: Additional Construct Descriptive Statistics

Table B1. Additional Construct Descriptive Statistics						
	Original			**Replication**		
Item	**Mean**	**SD**	**Loading**	**Mean**	**SD**	**Loading**
AWB1	6.238	0.771	0.79	5.25941	0.7557	0.849
AWB2	6.22	0.873	0.843	5.32636	0.79532	0.914
AWB3	6.32	0.812	0.855	5.30126	0.81041	0.823
AWB4	6.139	0.93	0.849	5.10042	0.92034	0.618
AWB5	6.126	0.945	0.854	5.0251	0.94346	0.569
CWB1	4.646	1.403	0.867	4.74477	1.41337	0.755
CWB2	4.851	1.419	0.824	5.33473	1.31127	0.839
CWB3	5.354	1.3	0.912	5.45188	1.3048	0.821
DE1	2.012	1.272	0.83	2.73222	1.48785	0.772
DE2	2.236	1.429	0.829	2.80753	1.65406	0.781
DE3	2.039	1.226	0.866	2.39331	1.43344	0.803
DE4	2.933	1.588	0.77	2.87866	1.72413	0.739
ENV1	2.029	1.276	0.816	3.51883	1.54439	0.803
ENV2	3.116	1.747	0.604	4.30126	1.5507	0.639
ENV3	1.9	1.277	0.806	3.27197	1.68947	0.837
ENV4	2.204	1.387	0.829	2.4728	1.5029	0.717
ENV5	2.204	1.483	0.766	3.36402	1.78383	0.753
ENV6	2.542	1.584	0.691	3.7113	1.87316	0.72
Extra1	4.112	1.585	0.931	4.09623	1.68132	0.755
Extra2	4.58	1.417	0.921	5.12971	1.45085	0.716

Table B1. Additional Construct Descriptive Statistics						
Neuro1	3.823	1.445	0.862	4.22176	1.63631	0.824
Neuro2	3.817	1.543	0.87	4.54812	1.47699	0.886
SE1	4.369	4.369	0.848	5.29289	1.4487	0.767
SE2	4.57	4.57	0.904	5.58577	1.2768	0.877
SE3	4.662	4.662	0.832	5.62343	1.24703	0.878
SIC1	5.617	1.722	0.744	5.57741	1.44117	0.711
SIC2	4.943	1.687	0.812	4.58577	1.70515	0.707
SIC3	4.597	1.566	0.838	5.01255	1.50484	0.844
SIC4	4.114	1.437	0.819	4.59414	1.57399	0.743
SIS1	4.291	1.531	0.831	4.99582	1.56242	0.726
SIS2	2.923	1.189	0.868	2.67364	1.18205	0.875
SIS3	2.874	1.434	0.875	2.68619	1.33704	0.654

Appendix C: Additional Path Coefficient Results

Table C1. Path Coefficients and Significance Levels for Control Variables				
Control Variable → Construct	**Envy on an SNS**		**Cognitive Well-Being**	
Result Type	**Original**	**Replication**	**Original**	**Replication**
SIS	0.045	0.071	-0.009	0.063
Age	-0.026	-0.079	-0.053	-0.144
DE	0.516**	0.318*	-	-
Extra	-0.085**	-0.24**	0.053	0.043
Gender	-0.033	0.019	-0.041	0.066
Neuro	0.021	0.095	-0.324**	0.063
Number of Friends	-0.02	-0.1	0.034	-0.158
Control Variable → Construct	**Affective Well-Being**		**Self-Enhancement on an SNS**	
Result Type	**Original**	**Replication**	**Original**	**Replication**
SIS	-0.044	-0.126*	0.218**	0.134*
Age	0.071**	0.108	-0.048	0.077
DE	-	-	-	-
Extra	0.051	-0.124	0.046	-0.023
Gender	0.017	-0.057	-0.120**	-0.168**
Neuro	-0.189**	-0.126**	0.023	-0.038
Number of Friends	-0.03	0.131	0.137**	0.135*

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