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Income More Reliably Predicts Frequent Than Intense Happiness

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Abstract

There is widespread consensus that income and subjective well-being are linked, but when and why they are connected is subject to ongoing debate. We draw on prior research that distinguishes between the *frequency* and *intensity* of happiness to suggest that higher income is more consistently linked to how *frequently* individuals experience happiness than how *intensely* happy each episode is. This occurs in part because lower-income individuals spend more time engaged in passive leisure activities, reducing the *frequency* but not the intensity of positive affect. Notably, we demonstrate that only happiness frequency underlies the relationship between income and life satisfaction. Data from an experience sampling study ($N = 394$ participants, 34,958 daily responses), a preregistered cross-sectional study ($N = 1{,}553$), and a day reconstruction study ($N = 13{,}437$) provide empirical evidence for these ideas. Together, this research provides conceptual and empirical clarity into how income is related to happiness.

Keywords

money, income, happiness, life satisfaction, time use

Philosophers and social scientists have long debated whether money makes people happier (Dunn et al., 2020).[1] A large body of work has focused on the ways spending money in the "right" ways improves happiness (Dunn et al., 2011; Greenberg & Hershfield, 2019; Matz et al., 2016; Whillans et al., 2017). Another body of research has focused on the relationship between income and happiness itself. Kahneman and Deaton (2010) find that higher income is only related to people's evaluation of their lives (i.e., life satisfaction) but not to happiness. Easterlin and colleagues (2010) find that happiness levels tend to remain static even as countries become richer, and a recent meta-analysis finds that "variations in wealth explain less than 1% of the variation in individual happiness" (Jantsch & Veenhoven, 2018; see also Hudson et al., 2016; Kushlev et al., 2015).

In light of income's robust relationship to life satisfaction (Donnelly et al., 2018; Jebb et al., 2018; Smeets et al., 2020; Stevenson & Wolfers, 2013) and the close mapping between happiness and life satisfaction (Cohn et al., 2009; Gamble & Gärling, 2012; Lyubomirsky et al., 2006), the current research asks: What makes the link between income and happiness so tenuous?

We address this question by bringing the *dynamics* of happiness into the spotlight. More specifically, we leverage research in the affective sciences, which suggests that happiness can be understood as consisting of two components (Davidson, 1998; Diener et al., 1985, 2009; Klonsky et al., 2019; Schimmack & Diener, 1997; Weidman & Dunn, 2016): (a) the *frequency* with which individuals experience happiness and (b) the *intensity* of each happiness episode. Our key premise is that income is more reliably linked to happiness *frequency* than happiness *intensity*; and consequently, that happiness frequency underlies the relationship between income and life satisfaction. These dynamic facets of happiness are often overlooked in prior research exploring the link between income and happiness and may therefore obscure important differences in how income predicts happiness.[2]

Our prediction that income will predict the frequency of happiness is grounded in prior research showing that how individuals spend their time differs by income. Specifically, lower-income individuals are more likely to spend their time engaged in passive (e.g., watching TV or relaxing) versus active (e.g., socializing or pursuing hobbies) leisure activities

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(Smeets et al., 2020; Whillans et al., 2017). The engagement in passive (vs. active) leisure activities, in turn, may be more likely to be subject to hedonic adaptation and therefore less likely to evoke happiness over time (O'Brien & Kassirer, 2019). Yet, active leisure has cumulative effects on well-being. For example, attending a religious service, practicing yoga, or exercising not only provides a positive boost in mood but can also result in higher overall well-being over time (Mochon et al., 2008).

Engaging in routine, intentional activities aimed at promoting happiness is especially likely to result in sustained happiness (Lyubomirsky et al., 2005). This is because they produce frequent, though transient, boosts in happiness—rather than intense feelings of happiness—that cumulatively improve well-being over time. Consequently, because lower-income individuals comparatively engage in more passive leisure activities, they are more likely to experience lower happiness frequency; and because higher income individuals comparatively engage in less passive leisure, they may be more likely to experience greater happiness frequency, given that the activities they typically complete are less subject to hedonic adaptation over time. This pattern of time use summarily suggests that income should positively predict happiness frequency.

Regarding the relationship between happiness frequency and life satisfaction, we draw on prior research which shows that the frequency and intensity of emotions—including happiness—may not have the same impact on individuals' life satisfaction (Diener et al., 1985; Schimmack & Diener, 1997). Indeed, previous research finds that the *frequency* of happiness is a stronger predictor of life satisfaction than the *intensity* of happiness (Diener et al., 2009). Experiencing happiness more frequently may help individuals to "broaden and build" their personal resources in a way that improves their life satisfaction to a great extent (Fredrickson, 2001). We therefore predict that happiness frequency underlies the link between income and life satisfaction.

We conducted three studies to provide evidence for our hypotheses. In Study 1, we assess happiness frequency and intensity in a 30-day daily diary study and relate these measures to income and life satisfaction (N = 394; 34,958 daily responses). In Study 2, we report the results of a preregistered cross-sectional study (N = 1,553), measuring happiness frequency and intensity, and relating both to income and life satisfaction. In Study 3, we leverage data from a day reconstruction study (N = 13,437) to corroborate these findings and provide evidence for the reduced engagement in passive (vs. active) leisure time as one mechanism underlying the relationship between higher income and increased happiness frequency.

Study 1

In Study 1, we report the results of a 30-day daily diary study that asks participants to report on their daily positive affect (PA) three times per day, as well as their income and life satisfaction.

Method

Participants

The sample was taken from the ongoing naturalistic study HowNutsAreTheDutch (Dutch: HoeGekIsNL; www.hownutsarethedutch.com; van der Krieke et al., 2016, 2017; henceforth "HND"). Because the happiness frequency measure could be confounded by the extent to which daily responses are missing within the sampling time frame, we excluded respondents with an insufficient number of responses. In particular, we excluded respondents for whom we did not have the equivalent of an average of one response per day (i.e., those with fewer than 30 responses) on the PA questions. (Our results hold when including these participants.) The final between-person sample size is 394 (M_{age} = 40.88, SD = 13.84; 80% female, 86% bachelor's degree or higher, 29% single-person household, 69% married, and 49% without children).

Measures

Income. Participants reported their individual monthly income (M = €2,610, SD = €1,172) via eight categories: "less than 750," "751–1,000," "1,001–1,500," "1,501–2,000," "2,001–2,500," "2,501–3,000," "3,001–3,500," and "more than 3,500." We coded income using the midpoint of the categorical range selected and used the natural log for analyses (e.g., Kahneman & Deaton, 2010).[3] Table S1 in the Online Appendix provides the distribution of the number of participants per income category in Study 1.

Happiness frequency and intensity. Positive affect ("PA") was measured by asking participants to rate their feelings on six adjective words: relaxed, energetic, enthusiastic, content, calm, and cheerful. These items were derived from prior research (see Feldman Barrett & Russell, 1998; Yik et al., 1999), and participants were asked to indicate the extent to which they felt each emotion (e.g., "I feel cheerful"). To calculate PA intensity and frequency, we used the procedure developed by Schimmack and Diener (1997) that proposes to remove the lowest level (i.e., 0) of PA meant to denote the relative absence of PA. We note that this procedure is commonly used with 7-point scales, for example, ranging from 0 to 6 (Schimmack & Diener, 1997) or from 1 to 7 (Carstensen et al., 2000, 2011). In these cases, the lowest levels of PA that are removed are "0" and "1," respectively. However, because the measurement of PA in our study included six items, each with a scale ranging from 0 to 100, participants almost never (4 of 34,958 responses) responded with "0" to all six items. This fact necessitated that we adapt the procedure by operationalizing the relative absence of PA as one SD below the mean level of PA.[4] The frequency of PA was then calculated as the number of episodes with PA above the threshold, divided by the total number of episodes. Following Schimmack and Diener (1997), we subsequently calculated happiness intensity as the average of the responses with values above this lowest level and happiness frequency as the average of the count of the daily responses with values above this lowest level.[5]

Table 1. Means, Standard Deviations, and Bivariate Correlations of Focal Variables (Study 1).

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Income	7.72	0.60								
2. PA frequency	0.86	0.16	.17**							
3. PA intensity	61.02	8.46	.10*	.60**						
4. Life satisfaction	4.92	1.11	.18**	.48**	.47**					
5. Age	40.88	13.84	.41**	.16**	.19**	−.01				
6. Female	0.80	0.40	−.11*	−.10*	−.05	.06	−.36**			
7. Education	7.24	1.00	.10	.08	−.02	.22**	−.22**	.05		
8. Married	0.69	0.46	.52**	.09	.10*	.28**	.08	.04	.07	
9. Number of children	1.06	1.19	.39**	.04	.07	.09	.57**	−.13**	−.08	.24**

Note. Income represents the log-transformed midpoint of the income category. Education was ordered by level of attainment (1 = *no education/elementary school not finished*, 2 = *elementary school or special education*, 3 = *primary or prevocational education*, 4 = *general secondary education*, 5 = *higher vocational education or vocational guidance education*, 6 = *higher general and pre-university education*, 7 = *higher professional education [bachelor]*, and 8 = *academic degree [master and PhD]*). PA = positive affect.
*p < .05. **p < .01. ***p < .001.

Table 2. Income Predicts Happiness Frequency But Not Happiness Intensity (Study 1).

	PA Frequency		PA Intensity	
Predictors	(1)	(2)	(3)	(4)
Income	.029** (.011)	.029* (.014)	0.004 (0.583)	−1.161 (0.760)
PA intensity	.011*** (.001)	.011*** (.001)		
PA frequency			31.129*** (2.151)	30.806*** (2.171)
Age		.001 (.001)		0.077* (0.035)
Female		−.021 (.017)		0.830 (0.920)
Education		.016* (.007)		−0.381 (0.359)
Married		−.005 (.017)		1.527 (0.890)
Number of children		−.010 (.007)		−0.049 (0.362)
Constant	−.054 (.093)	−.157 (.115)	34.351*** (4.588)	41.573*** (5.672)
Observations	394	394	394	394
R^2	.367	.383	.355	.374

Note. Standard errors are in parentheses. Income represents the log-transformed midpoint of the income category. Education was ordered by level of attainment (1 = *no education/elementary school not finished*, 2 = *elementary school or special education*, 3 = *primary or prevocational education*, 4 = *general secondary education*, 5 = *higher vocational education or vocational guidance education*, 6 = *higher general and pre-university education*, 7 = *higher professional education [bachelor]*, and 8 = *academic degree [master and PhD]*). PA = positive affect.
*p < .05. **p < .01. ***p < .001.

Life satisfaction. Following the daily diaries, life satisfaction was assessed using a single-item measure, "How satisfied are you with your life as a whole" (1 = *couldn't be worse*, 7 = *couldn't be better*; see Priebe et al., 1999).

Controls. We control for variables previously associated with our variables of interest including age, gender, education, marital status, and the number of children.

Results

Bivariate correlations are displayed in Table 1.

Income Predicts Happiness Frequency

Ordinary least squares (OLS) regressions reveal that the relationship between income and happiness frequency is statistically significant and positive ($b = 0.03$, $SE = .01$, $p = .008$, $r = .13$; see Table 2), while income is not a statistically significant predictor of happiness intensity ($b = 0.004$, $SE = .58$, $p = .995$, $r = .00$; see Table 2). When controlling for a conventional battery of covariates, income remains a statistically significant and positive predictor of happiness frequency ($b = 0.03$, $SE = .01$, $p = .044$, $r = .10$; see Table 2), but not of happiness intensity ($b = -1.16$, $SE = .76$, $p = .127$, $r = .08$; see Table 2).[6] The variance inflation factors (VIFs) are less than 3 in the above models, suggesting that the models are not subject to multicollinearity issues.

Indirect Path From Income to Life Satisfaction Through Happiness Frequency

We next tested the relationship between income, happiness frequency/intensity, and life satisfaction. This analysis revealed that both happiness frequency ($b = 2.13$, $SE = .37$, $p < .001$, $r = .28$) and happiness intensity ($b = 0.04$, $SE = .01$, $p < .001$, $r = .26$) are positively related to life satisfaction. To test for the indirect relationships between income and life satisfaction via happiness frequency and happiness intensity, we conducted a multipath analysis, simultaneously regressing both happiness frequency and happiness intensity as potential statistical mediators. Significance tests with 10,000 bootstraps show that—consistent with the broaden-and-build theory of positive emotions (Fredrickson, 2001)—only happiness frequency underlies the relationship between income and life satisfaction ($b = 0.06$, $SE = .03$, $p = .047$, 95% CI [.008, .126]), while happiness intensity does not ($b = -0.02$, $SE = .03$, $p = .639$, 95% CI [−.079, .047]).

Discussion

Study 1 provides tentative support for our hypothesis that income is uniquely related to happiness frequency and that this link is related to life satisfaction. Although the daily responses provided us with a measure of happiness frequency, we cannot ascertain whether individuals actually realize that they frequently experience happiness. In addition, given that the scale used to measure PA did not allow us to clearly identify the absence of PA, our measurements of happiness frequency and happiness intensity were somewhat noisy. We address this concern in Study 2 which employs a validated tool to directly measure happiness frequency and intensity.

Study 2

Study 2 aimed to carefully examine the link between income, happiness frequency and intensity, and life satisfaction. Notably, this study employs a large sample size, validated measures of happiness frequency and happiness intensity, and a preregistered design to carefully test for not only a relationship between income and happiness frequency but also a null relationship between income and happiness intensity.

Method

Analysis Plan

We perfectly followed our preregistered analysis plan and exclusion rules. The preregistration can be found at https://osf.io/9zqem

Participants

We used a simulation approach to conduct a power analysis for the path model with parallel mediation paths, setting the sample size at a level that is sufficient to detect even a small effect ($r = .1$ or Cohen's $d = .2$) for each path, which revealed that a sample size of 1,260 participants would be needed. The code for the power analysis can be found at our Open Science Framework repository. Given the 35% exclusion rate estimated from our pilot study, we aimed to recruit 2,000 participants through Amazon's Mechanical Turk, and 1,982 participants completed the entire survey.

Toward the end of the survey, participants were asked to read a simple essay about a holiday trip and then answered five multiple-choice questions related to the details of the trip described in the essay. As preregistered, only participants who answered all five questions correctly were included in the analysis, yielding a final sample size of 1,290 adults ($M_{age} = 39.83$, $SD = 12.94$, 58% female, 55% have a bachelor's degree or higher).

Measures

Income. We measured annual household income ($M =$ USD\$42,637, $SD =$ USD\$31,141) with a 30-category measure ranging from "less than \$10,000" to "\$500,000 and above." Note that income in Study 2 was measured as household income. As preregistered, and consistent with Study 1 to ascertain income per capita, income was transformed to be pseudo-continuous using the midpoints of each bracket, then divided by the square root of the number of household members before being logged (e.g., see Kahneman & Deaton, 2010). Table S2 in the Online Appendix provides the distribution of the number of participants per income category in Study 2.

Happiness frequency and intensity. We assessed the two happiness dimensions through the Multidimensional Emotions Questionnaire (see Klonsky et al., 2019). Happiness was assessed by its frequency ("How often you experience the emotion") and intensity ("How intense the emotion typically is when it occurs"). The response choices for the happiness dimensions were as follows: (a) frequency: "about once each month," "about once each week," "about once each day," "about 2–3 times each day," and "more than 3 times each day" and (b) intensity: "very low," "low," "moderate," "high," and "very high."

Life satisfaction. After reporting on their happiness frequency and intensity, we assessed life satisfaction with the 5-item *Satisfaction with Life* Scale (Diener et al., 1985). Participants rated their agreement (1 = *strongly disagree*, 5 = *strongly agree*) with each item on a 5-point scale ($\alpha = .93$), including "In most ways, my life is close to ideal" and "The conditions of my life are excellent."

Demographic controls. We preregistered that we would control for employment status, age, gender, race, and education—variables that have been associated with happiness and life satisfaction in prior research. For the sake of open practices, analyses including and excluding demographic controls are reported.

We also preregistered two additional control variables, happiness persistence ("How long-lasting the emotion typically is when it occurs") and the ease with which people can regulate their happiness (henceforth "happiness regulation"; "How well you can regulate the emotion when it occurs"). The response

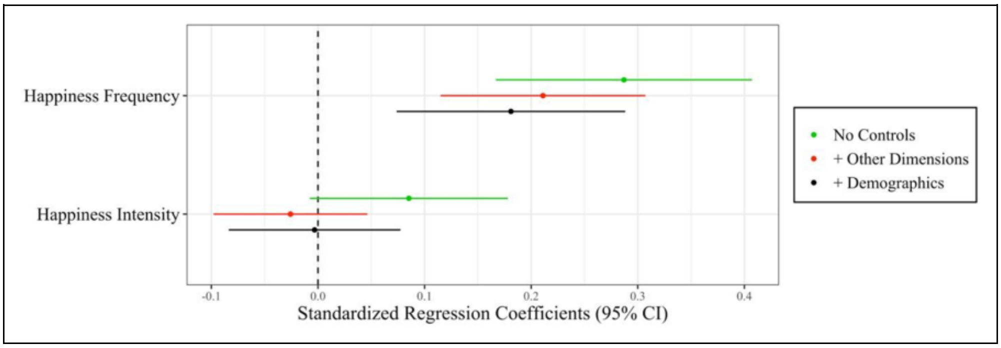

Figure 1. Dot-whisker plot for the relationships between income and happiness frequency/intensity (Study 2). *Note.* The relationship between income and happiness frequency is statistically significant; the relationship between income and happiness intensity is not. Table S3 in the Online Appendix contains the full model specifications. Green lines depict results without covariates, red lines depict results controlling for other happiness dimensions, and black lines depict results controlling for other happiness dimensions and demographic controls.

for happiness persistence and regulation were as follows: (a) persistence: "less than 1 min," "1–10 min," "11–60 min," "1–4 h," and "longer than 4 h" and (b) regulation: "very easy," "easy," "moderate," "difficult," and "very difficult." We control for happiness persistence and happiness regulation in our preregistered analysis, but all results hold when we exclude these measures.

Results

Bivariate correlations are displayed in Table S4 in the Online Appendix.

Income Predicts Happiness Frequency

OLS regressions reveal that the relationship between income and happiness frequency was statistically significant and positive, as predicted ($b = 0.20$, $SE = .04$, $p < .001$, $r = .13$; see Table S5 in the Online Appendix, Model 1), whereas the relationship between income and happiness intensity was not statistically significant, $b = 0.06$, $SE = .03$, $p = .073$, $r = .05$ (see Table S5 in the Online Appendix, Model 4).[7] To rule out the possibility that the (null) relationship between income and happiness intensity was due to the interrelation among happiness dimensions, we conducted regressions controlling for the other dimensions of happiness (VIFs in all regressions were below 2). In this analysis, income remained a statistically significant and positive predictor of happiness frequency ($b = 0.15$, $SE = .03$, $p < .001$, $r = .12$; see Table S5 in the Online Appendix, Model 2), while income continued to have no statistically significant relationship with happiness intensity ($b = -0.02$, $SE = .03$, $p = .483$, $r = .02$; see Table S5 in the Online Appendix, Model 5). Figure 1 provides a graphical representation of these results.

Quantifying Evidence in Favor of the Null for Other Happiness Facets

To quantify the evidence in favor of the null relationship between income and happiness intensity, we employed Bayesian regressions with noninformative priors to construct credibility intervals of the regression coefficients (Wagenmakers et al., 2016). Results of Bayesian regressions with the *Rstanarm* package in *R* (Goodrich et al., 2019) show that the 95% credibility interval for the coefficient of income on happiness frequency does not include zero ([.120, .280]), whereas in contrast, the credibility intervals for happiness intensity (95% CI [−.005, .123]) includes zero.[8]

We next reran Bayesian regressions controlling for the other happiness dimensions, and the results remain similar, such that the 95% credibility interval of the relationship between income and happiness frequency does not include zero (95% CI [.078, .215]), while the credibility intervals for happiness intensity (95% CI [−.069, .032]) includes zero. Thus, we can conclude that there is a 95% chance that the relationship between income and happiness frequency differs from zero, while evidence is lacking to draw similar conclusions for happiness intensity.[9]

Although not preregistered, we also explored further evidence for the null relationships with the region of practical equivalence (ROPE) approach (Kruschke & Liddell, 2018), which provides evidence for null relationships by examining whether the 90% highest density interval (HDI) lies outside of ROPE (the negligible area around the null value). Analysis reveals that there is 0% overlapping between the 90% HDI and the ROPE for happiness frequency, whereas in contrast, there is a large percentage overlap between the HDI and the ROPE for happiness intensity (83.3%). Controlling for the other happiness dimensions yields similar results, such that there is 10.1% overlapping between the 90% HDI and the ROPE for happiness frequency, whereas in contrast, the 90% HDI completely (100%) lies within the ROPE for happiness intensity. While the 90% HDI for each happiness dimension did not consistently meet the conventional cutoff of 0% (to accept a null relationship) or 100% (to reject a null relationship) across all model specifications, the overall pattern of the overlapping between HDI and ROPE suggest moderate evidence in favor of the relationship between income and happiness frequency and the null relationship between income and happiness intensity.

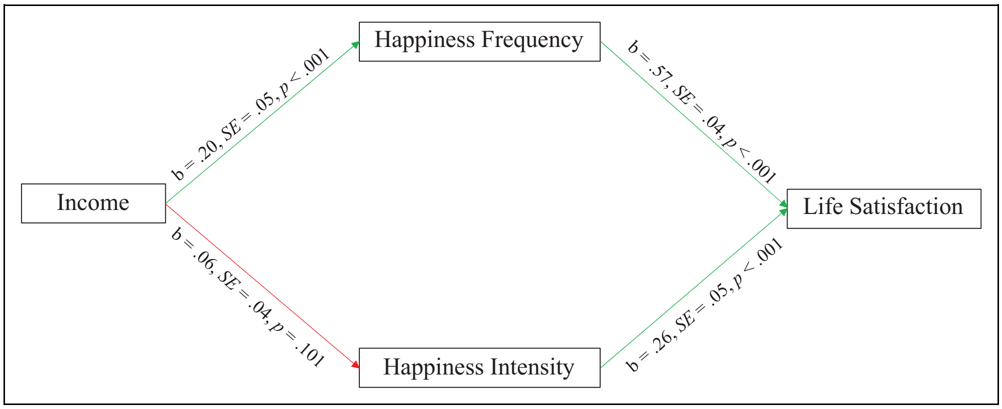

Figure 2. Results of parallel path analysis linking income to life satisfaction through happiness frequency and happiness intensity (Study 2). *Note.* Only the path linking income to life satisfaction through happiness frequency is statistically significant, while the other path is not. Statistically significant paths are in green and nonsignificant paths are in red.

Indirect Path From Income to Life Satisfaction Through Happiness Frequency

We next tested which happiness dimensions underlie the relationship between income and life satisfaction. We first regressed life satisfaction on the happiness facets, and found that both happiness frequency ($b = 0.61$, $SE = .04$, $p < .001$, $r = .39$) and happiness intensity ($b = 0.25$, $SE = .05$, $p < .001$, $r = .12$) are positively related to life satisfaction. As preregistered, we next conducted a path analysis within structural equation modeling to test which dimensions of happiness statistically underlie the relationship between income and life satisfaction. In the multipath model, we focused on happiness frequency and happiness intensity as mediators between income and life satisfaction and tested the indirect relationship using 10,000 bootstraps. The path coefficients are displayed in Figure 2. Significance tests of the indirect relationships supported our hypothesis that happiness frequency underlies the relationship between income and life satisfaction ($b = 0.11$, $SE = .03$, $p < .001$, 95% CI [.062, .166]), whereas happiness intensity ($b = 0.02$, $SE = .01$, $p = .134$, 95% CI [−.002, .038]) does not.[10]

Discussion

Studies 1 and 2 provide convergent evidence that income predicts happiness frequency as well as validating the null relationship between income and happiness intensity. However, these studies do not shed insight into a potential mechanism underlying the relationship from income to happiness frequency, which we explored in Study 3.

Study 3

In Study 3, we aimed to test whether the relationship between income and happiness frequency can be explained by differences in time use, specifically, in passive (vs. active) leisure activities.

Method

Data come from the 2012–2013 American Time Use Survey (ATUS) conducted by the Bureau of Labor Statistics, which incorporated a Well-Being Module (WBM) that assesses respondents' overall life satisfaction and affective experience. Specifically, the WBM implements a Day Reconstruction Method (DRM) in which respondents are asked to define episodes of their waking hours of the day before the interviewing day and then to rate their feelings corresponding to three randomly selected episodes. The 2012–2013 WBM includes over 20,000 respondents and has been validated in previous research (Dolan et al., 2017; Kushlev et al., 2015; Lee et al., 2016). Of the 20,000 respondents, 13,437 ($M_{\text{age}} = 43.46$, $SD = 13.24$, 51% female, 41% have a bachelor's degree or higher, 19% non-White, 52% married, 56% without children) had at least two within-person episode responses and completed all individual-level focal variables required for analyses.

Income

The ATUS measured annual family income (M = USD$36,291, SD = USD$18,691) using 16 categories ranging from "less than $5,000" to "$150,000 and above." We transformed income to be pseudo-continuous using the midpoints of each bracket, then divided by the square root of the number of household members to ascertain income per capita before being logged (e.g., Kahneman & Deaton, 2010). Table S3 in the Online Appendix provides the distribution of the number of participants per income category in Study 3. Note that if we code income as a continuous variable ranging from 1 to 16 (for each income bracket), the subsequent results are substantively similar (see Table S6 in the Online Appendix for more details).

Active and Passive Leisure Time Use

Following the operationalization of leisure time used in prior literature (Smeets et al., 2020), we calculated the frequency of episodes spent on praying, socializing, exercise, hobbies,

Table 3. Means, Standard Deviations, and Bivariate Correlations of Focal Variables (Study 3).

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Income	10.31	0.70													
2. Happiness frequency	2.90	0.35	.04**												
3. Happiness intensity	4.54	1.11	−.08**	.11**											
4. Active leisure	0.05	0.06	.04**	.04**	.08**										
5. Passive leisure	0.22	0.11	−.11**	−.05**	.02**	−.16**									
6. Age	43.46	13.24	.20**	−.02*	.04**	−.00	.03**								
7. Female	0.51	0.50	−.08**	−.01	.05**	−.02	−.15**	−.00							
8. Education	3.79	1.72	.39**	.07**	−.12**	.06**	−.21**	.06**	.04**						
9. Non-White	0.19	0.40	−.10**	−.06**	.08**	−.02**	.09**	−.02*	.07**	−.01					
10. Full-time employment	0.94	0.24	.23**	.01	−.00	−.01	−.08**	.02*	−.02*	.11**	−.05**				
11. Married	0.52	0.50	.14**	.06**	.06**	.03**	−.09**	.11**	−.10**	.14**	−.14**	.08**			
12. Number of children	0.80	1.07	−.20**	.04**	.03**	−.03**	−.13**	−.26**	.01	.06**	−.05**	.01	.38**		
13. Weekend	0.35	0.48	.00	.02	.03**	.04**	.01	−.02*	−.00	.01	−.00	−.00	−.00	.01	
14. Average activity time	189.17	103.80	−.09**	−.01	−.01	.03**	.25**	−.17**	.02*	−.05**	.07**	−.08**	−.16**	−.07**	.07**

Note. Income represents the log-transformed quotient of the income category midpoint and the square root of household size. Education was ordered by level of attainment (1 = *12th grade—no diploma or below*, 2 = *high school graduate*, 3 = *some college but no degree*, 4 = *associate degree*, 5 = *bachelor's degree*, 6 = *master's degree*, 7 = *professional school degree*, and 8 = *doctoral degree*). Year 2012 is the omitted category.
*$p < .05$. **$p < .01$. ***$p < .001$.

Table 4. Income Predicts Happiness Frequency But Not Happiness Intensity (Study 3).

	Happiness Frequency				Happiness Intensity			
Predictors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Income	.026*** (.004)	.012* (.005)	.023*** (.004)	.011* (.005)	−.142*** (.014)	−.080*** (.016)	−0.141*** (.014)	−0.080*** (.016)
Happiness intensity	.037*** (.003)	.040*** (.003)	.036*** (.003)	.040*** (.003)				
Happiness frequency					.378*** (.028)	.405*** (.027)	0.375*** (.028)	0.399*** (.027)
Active leisure			.103* (.050)	.081 (.050)			1.495*** (.160)	1.589*** (.158)
Passive leisure			−.165*** (.028)	−.107*** (.030)			0.380*** (.091)	0.271** (.096)
Age		−.001*** (.0002)		−.001*** (.0002)		.005*** (.001)		0.005*** (.001)
Female		−.004 (.006)		−.007 (.006)		.116*** (.019)		0.127*** (.019)
Education		.015*** (.002)		.014*** (.002)		−.086*** (.006)		−0.087*** (.006)
Non-White		−.057*** (.008)		−.055*** (.008)		.261*** (.024)		0.261*** (.024)
Full-time employment		−.009 (.012)		−.010 (.012)		.090* (.040)		0.101* (.040)
Married		.022** (.007)		.022** (.007)		.194*** (.022)		0.186*** (.022)
Number of children		.002 (.003)		.002 (.003)		.010 (.010)		0.017 (.010)
Weekend		.007 (.006)		.007 (.006)		.077*** (.020)		0.070*** (.020)
Activity duration		−.00001 (.00003)		.00001 (.00003)		−.00001 (.0001)		−0.0001 (.0001)
Year: 2013		−.007 (.006)		−.007 (.006)		−.010 (.019)		−0.011 (.019)
Constant	2.466*** (.046)	2.596*** (.052)	2.529*** (.047)	2.627*** (.052)	4.902*** (.159)	3.983*** (.176)	4.754*** (.163)	3.870*** (.178)
Observations	13,437	13,437	13,437	13,437	13,437	13,437	13,437	13,437
R^2	.016	.028	.019	.029	.021	.054	.028	.061

Note. Standard errors are in parentheses. Income represents the log-transformed quotient of the income category midpoint and the square root of household size. Education was ordered by level of attainment (1 = *12th grade—no diploma or below*, 2 = *high school graduate*, 3 = *some college but no degree*, 4 = *associate degree*, 5 = *bachelor's degree*, 6 = *master's degree*, 7 = *professional school degree*, and 8 = *doctoral degree*). Year 2012 is the omitted category. PA = positive affect.
*p < .05. **p < .01. ***p < .001.

Table 5. Income Predicts Passive Leisure (Study 3).

	Active Leisure		Passive Leisure	
Predictors	(1)	(2)	(3)	(4)
Income	.004*** (.001)	.001 (.001)	−.016*** (.001)	−.008*** (.001)
Age		−.0001* (.00004)		.001*** (.0001)
Female		−.001 (.001)		−.034*** (.002)
Education		.002*** (.0003)		−.010*** (.001)
Non-White		−.003** (.001)		.019*** (.002)
Full-time employment		−.005* (.002)		−.011** (.004)
Married		.005*** (.001)		−.001 (.002)
Number of children		−.003*** (0.001)		−.009*** (.001)
Weekend		.004*** (.001)		−.001 (.002)
Activity duration		.00002** (.00001)		.0002*** (.00001)
Year: 2013		.002 (.001)		−.005** (.002)
Constant	.008 (.008)	.031*** (.009)	.381*** (.013)	.296*** (.014)
Observations	13,437	13,437	13,437	13,437
R^2	.002	.009	.011	.151

Note. Standard errors are in parentheses. Income represents the log-transformed quotient of the income category midpoint and the square root of household size. Education was ordered by level of attainment (1 = *12th grade—no diploma or below*, 2 = *high school graduate*, 3 = *some college but no degree*, 4 = *associate degree*, 5 = *bachelor's degree*, 6 = *master's degree*, 7 = *professional school degree*, and 8 = *doctoral degree*). Year 2012 represents the omitted category.
*p < .05. **p < .01. ***p < .001.

volunteering, watching TV, relaxing, and sleeping from the ATUS data. Following prior work, we defined "active leisure" as the composite of the frequencies of praying, socializing, exercise, hobbies, volunteering, and "passive leisure" as the composite of watching TV, relaxing, and sleeping.

Happiness Frequency and Intensity

The ATUS assessed happiness by asking, "From 0 to 6, where 0 means you were not happy and 6 means you were very happy, how happy did you feel at this time?" Following prior research (Schimmack & Diener, 1997), responses with the value of 0 (reflecting the absence of happiness) were removed in the calculation of happiness frequency and happiness intensity. Specifically, we calculated frequency as the number of episodes in which respondents had nonzero ratings of this question, and we calculate intensity as the average of the values of happiness excluding the lowest value (i.e., 0) across three episodes.

Controls

We control for variables previously associated with life satisfaction, including age, gender, race, education, marital status, and work hours. In addition, we control for financial insecurity (Kushlev et al., 2015; Whillans et al., 2016), employment status, the number of children, and day of week participants responded to the study—control used in prior research (Stone et al., 2018). We also controlled for the average duration of the activities.

Results

Bivariate correlations are displayed in Table 3.

Income Predicts Happiness Frequency

OLS regressions reveal that the relationship between income and happiness frequency is statistically significant and positive as predicted ($b = 0.03$, $SE = .004$, $p < .001$, $r = .05$; see Table 4). In contrast, income is negatively associated with happiness intensity: $b = -0.14$, $SE = .01$, $p < .001$, $r = .09$ (see Table 4). When controlling for covariates, income remains a statistically significant and positive predictor of happiness frequency ($b = 0.01$, $SE = .01$, $p = .019$, $r = .02$), and a significant and negative predictor of happiness intensity ($b = -0.08$, $SE = .02$, $p < .001$, $r = .04$).[11] The VIFs are less than 2 in the above models, suggesting that the models are not subject to multicollinearity concerns.

Passive Leisure Time Use as One Mechanism Linking Income and Happiness Frequency

We next explored whether time spent on leisure activities underlies the relationship between income and happiness frequency. First, we examined the relationship between leisure time use and happiness frequency and intensity. Analysis revealed that only the relationship between passive leisure and happiness frequency was statistically significantly when including controls ($b = -0.11$, $SE = .03$, $p < .001$, $r = .03$; see Table 4), while the relationship between active leisure and happiness frequency ($b = 0.08$, $SE = .05$, $p = .105$, $r = .01$) was not. In terms of happiness intensity, the relationship between active leisure and happiness intensity ($b = 1.59$, $SE = .16$, $p < .001$, $r = .08$) and passive leisure and happiness intensity ($b = 0.27$, $SE = .10$, $p = .005$, $r = .02$) was positive and statistically significant. That is, increased passive leisure time use is associated with lower levels of happiness frequency but not happiness intensity, consistent with our prediction.

Second, to test for the relationship between income and leisure, we conducted OLS regressions of active and passive leisure on income. Analysis revealed that only the relationship between income and passive leisure was statistically significant when including controls ($b = -0.008$, $SE = .001$, $p < .001$, $r = .05$; see Table 5), while the relationship between income on active leisure was not ($b = 0.001$, $SE = .001$, $p = .172$, $r = .01$). That is, lower levels of income were related to higher levels of passive leisure time use, consistent with previous research (Smeets et al., 2020).

Indirect Path From Income to Happiness Frequency Through Passive Time Use

We subsequently tested whether passive leisure time use statistically underlies the relationship between income and happiness frequency. To do so, we constructed a path model with structural equation modeling and tested the indirect relationship with 10,000 bootstraps. Analyses reveal that passive leisure statistically underlies the relationship between income and happiness frequency ($b = 0.003$, $SE = .001$, $p < .001$, 95% CI [.002, .004]), providing evidence for one underlying mechanism linking income to happiness frequency. In an additional exploratory analysis, we tested an alternative path to examine the strength of our evidence, comparing our path model to one in which the predictor and mediator are switched. The results show that our hypothesized path model has a better fit than this alternative model, income predicts happiness frequency through passive leisure: $\chi^2(1) = 18.89$, $p < .001$, confirmatory fit index [CFI] = .91, Root Mean Square Error of Approximation [RMSE] = .04; income predicts passive leisure through happiness frequency: $\chi^2(1) = 144.64$, $p < .001$, CFI = .31, RMSE = .10.

Supplementary Analysis

Although we controlled for various demographic variables in our regression models, the fact that education and marital status are also correlated with happiness frequency (as indicated by Table 4) may raise concerns that the relationship between income and happiness frequency is less strong. We therefore compared the extent to which income versus education and marital status predict happiness frequency across the three studies. Notably, the coefficients for income are stably statistically significant across all three studies (see Table S10 in the Online Appendix). In contrast, the coefficients for education and marital status are not statistically significant in Study 2 and Study 1, respectively. In one study (Study 2), the coefficient for education is significantly smaller than the coefficient for income ($b_{\text{difference}} = 0.09$, $SE = .05$, $p = .050$). Taken together, income appears to be more reliably linked to happiness frequency than other key demographic variables (i.e., education and marital status).

Discussion

In Study 3, we replicated the findings of Studies 1 and 2 with a more representative sample. Moreover, we identified passive leisure time use as one mechanism underlying the relationship between income and happiness frequency, such that low-income individuals were more likely to spend time on passive leisure, which in turn predicted lower happiness frequency.

General Discussion

Money is believed to bring about greater satisfaction in life. While the relationship between income and happiness has received a great deal of attention (Donnelly et al., 2018; Jebb et al., 2018; Kahneman & Deaton, 2010; Smeets et al., 2020; Stevenson & Wolfers, 2013), the current work inquired into the role of the dynamics of happiness—frequency and intensity—in the relationship between income and life satisfaction. Across three studies, income was consistently positively related to happiness frequency, and happiness frequency in part explained the relationship between income and life satisfaction due to decreased passive leisure.

The current article contributes to the literature on income and subjective well-being. First, while prior work has found a robust link between income and life satisfaction, the link between income and happiness is more tenuous (Donnelly et al., 2018; Jebb et al., 2018; Smeets et al., 2020; Stevenson & Wolfers, 2013). In the current research, we highlight that one way to resolve this tension is to bring the dynamics of happiness into the foreground. We advance our understanding of how income may affect the ways happiness is experienced—how frequently, more so than how intensely—a distinction that provides one puzzle piece to explain prior mixed findings between income and happiness. Second, we build on recent work that explores how the relationship between spending and happiness depends on how happiness is defined (Aknin et al., 2020; Weidman & Dunn, 2016). Consider that one recent study found that how people spend money—for example, on material or experiential purchases—may have distinct effects on the frequency and intensity of happiness (Weidman & Dunn, 2016). Approaches that explore these dynamic components of happiness over time may allow future work to move beyond one-dimensional conceptualizations of happiness and unpack how money and spending shape affective and temporal dimensions of happiness, and in turn, overall well-being. Finally, one of the implications of our findings is that inequalities in happiness by income may persist because low-income individuals are more likely to engage in passive leisure activities (see also Smeets et al., 2020). To address such inequalities, future research could examine ways to nudge low-income individuals away from passive leisure activities and toward uses of time that yield greater meaning.

The present work has several limitations. First, despite the consistency in our findings across studies, like most other work on subjective well-being, we rely on correlational and cross-sectional data. We urge future research to leverage experimental designs that directly manipulate happiness frequency (e.g., through carefully timed unconditional cash transfers; Haushofer & Shapiro, 2016) or natural experiments to further tease apart causality and allow for careful examination of the temporal dynamics of time use and happiness frequency. Second, while our samples were large and diverse, only Study 3 was representative. Indeed, while we draw inferences from a diversity of samples, it is unlikely that our studies are able to adequately capture very high-income individuals—those at the very top of the income distribution (Smeets et al., 2020). Finally, as thoughts about the value of money and leisure vary greatly across cultures (Diener & Lucas, 2000; Macchia & Whillans, 2019), we might have drawn different conclusions if our studies had drawn from non-Western societies, a possibility that future research should explore.

In sum, the current research sheds light on why the relationship between income and happiness is so tenuous. Three studies provided evidence that a critical unexplored mechanism—happiness frequency—provides a crucial puzzle piece to better understand this relationship: Higher income people experience less passive leisure and therefore greater happiness frequency, which in turn promotes greater life satisfaction. Taken together, income may bring about happiness not through more intensely happy experiences, but through a greater number of them.

Authors' Note

Data, code, and preregistration available at https://osf.io/e2f4d/?view_only=d31ac75c183944a282f2d5407d9a87b3

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Supplemental Material

The supplemental material is available in the online version of the article.

Notes

1. Following prior research (Greenberg & Mogilner, 2020; Mogilner et al., 2018), we define life satisfaction as the cognitive component of subjective well-being (i.e., people's evaluation of their lives) and positive affect (PA; i.e., happiness) as the affective component (see also Diener, 1994; Jebb et al., 2018).
2. We note that some prior work has explored how income is related to day-level happiness but does not distinguish between different components of such happiness dynamics. For example, previous research has found that day-to-day happiness does not rise after a modest satiation point in income (Jebb et al., 2018; Kahneman & Deaton, 2010).
3. We follow the typical standard from economics as well as recommendations in prior research to use the bracket midpoint (which is done primarily out of necessity because most surveys use income bins rather than open-ended self-reports) and log-transform incomes reported on such scales (e.g., Boyce et al., 2010; Frijters et al., 2004; Kahneman & Deaton, 2010).
4. We note that the results presented here also hold when the cutoff is set at 0.5 *SD* below the mean of PA (see Table S9 in the Supplementary Information). We also considered a cutoff at 2 *SD* below the mean. However, such a cutoff would yield insufficient variance in PA frequency; 98% of all responses would be categorized as having a presence of PA (in contrast to 90% of all responses with a cutoff of 1 *SD* and 78% with a cutoff of 0.5 *SD*).
5. We conducted a Kolmogorov–Smirnov test to explore the distribution of happiness frequency and intensity, which revealed that happiness intensity is normally distributed while happiness frequency is negatively skewed. Importantly, the results reported below hold when using a square transformation to happiness frequency.
6. These results also hold when controlling for the average level of PA. Because of the collinearity of PA mean and PA intensity (variance inflation factor [VIF] > 10), results based on models that include PA mean are difficult to interpret. Nevertheless, including PA mean does not appear to substantially affect the results presented here (see Table S7 in the Online Appendix).
7. Income is not related to happiness persistence ($b = -0.03$, $SE = .03$, $p = .453$, $d = .04$; see Table S5 in the Online Appendix, Model 8) or happiness regulation ($b = -0.03$, $SE = .04$, $p = .367$, $d = .05$; see Table S5 in the Online Appendix, Model 11). These results also held when additionally controlling for demographic variables.
8. The 95% credibility intervals for the coefficients relating income to happiness persistence (95% CI [−.033, .115]) or happiness regulation (95% CI [−.129, .006]) include zero.
9. Similarly, we do not find sufficient evidence for the relationships between income and happiness persistence (95% CI [−.090, .043]) and happiness regulation (95% CI [−.099, .034]).
10. The indirect relationships via happiness persistence ($b = 0.01$, $SE = .01$, $p = .330$, 95% CI [−.004, .020]) and happiness regulation ($b = 0.002$, $SE = .003$, $p = .491$, 95% CI [−.002, .013]) are not significant.
11. Similar to Study 1, we did not control for the average level of happiness here due to multicollinearity concerns (VIFs > 7). Nevertheless, controlling for the average level of happiness does not substantively alter our results (see Table S8 in the Online Appendix).

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