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Social Media and Transition into Adulthood: A Life-Course Approach

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Introduction

The digital revolution has radically reshaped youth opportunities and risks in society. In particular, social media has transformed the way young people manage their privacy and self-expression (Livingstone & Third, 2017), negotiate their identity and peer norms (Boyd, 2014), establish personal and intimate relationships (Turkle, 2011) and access jobs (Helsper, 2021). In the demographic literature, scholars have addressed how the expansion of internet and media coverage link to variations in young people's outcomes and life chances. For example, Billari and collegues (2019) examined how the expansion of high-speed internet impacts on fertility behaviours. Using a similar approach, Sironi and Kashyap (2022) investigated the existing age-dependent relationship between internet access and partnership formation. Yet, to date, the demographic literature is missing a bigger picture on how exposure to social media shapes the timing and attainment of critical markers of the transition to adulthood.

In this paper, we contribute to existing demographic literature by developing a novel integrated life-course approach to study the way different forms of social media exposure affect the timing and processes associated with the transition to adulthood. The transition into adulthood encompasses a dynamic stage in which individuals progressively assume stereotypical adult roles and responsibilities, including completing education, leaving the parental home, entering the labour market, forming partnerships and having children. While previous research has documented how variability in the timing and sequencing of this transition is influenced by individual choices and broader societal factors (Billari & Liefbroer, 2010; Elder, 1975; Furstenberg Jr. et al., 2005; Settersten Jr. & Ray, 2010), how social media exposure may shape the transition to adulthood is largely unknown. Young people today are digital natives, representing cohorts that are entirely socialised by social media and digital platforms (Livingstone & Third, 2017). As these generations are today experiencing the transition to adulthood in digitalised societies, it is essential to identify whether variations in social media use influence key life-course events associated with the transition to adulthood.

Our study focuses on the Netherlands, which ranks among the leading European countries in terms of internet penetration, with over 98% of the population having access, compared to the EU average of 94.2% (Eurostat, 2024). The Dutch context is also characterized by relatively smooth and rapid transitions to adulthood, particularly in comparison to Southern European countries (Schwanitz, 2017). However, more recently, the country has shown decreases in the expansion of higher education, stable unemployment, increased percentage of NEETs, and about a one year-delay in the exit from parental home, compared to the past decade, precisely when social media platforms have become much more salient in society (Eurostat, 2024).

Our paper seeks to answer three research questions (RQs): RQ1. How do the timings of key transitional events to adulthood differ between social media users and non-users?; RQ2. To what extent do specific forms of social media exposure causally affect the achievement of major transitional milestones in young adulthood?; and RQ3. How can social media users be categorised into distinct user profiles, and how do these profiles differ in the transition into adulthood?

Data and methods

This study leverage LISS (Longitudinal Internet Studies for the Social Sciences), a panel dataset from the Netherlands that collects information for 5000 households, designed to be representative of the Dutch population aged 16 and over. We use the data from Wave 7 to 17, covering the period 2014-2024. The most relevant module from LISS for this study is "Social Integration and Leisure".

This module provides extensive information on digital access, social media use, and frequency of use of major social media platforms, measured on a Likert scale (e.g., Facebook, Instagram, LinkedIn, X, YouTube, Snapchat, Telegram, WhatsApp, Twitch, TikTok, Discord, Pinterest). These detailed measures allow researchers to investigate variations regarding patterns of social media use and different types of online users. For each transitional phase, we draw a sub-sample of individuals from the whole LISS (N=13302 individuals), obtaining a sample of N=732 individuals for transition to higher education, N=1919 individuals for transition to work, N=99 individuals for transition to independent living, N=152 individuals for transition to cohabitation, N=236 individuals for transition to parenthood.

Our empirical strategy follows different steps. We first use Kaplan-Meier models to analyse the trends in the timing of transitional events comparing social media users to non-users. To examine whether transitions differ by type of social media use, we employ pooled Latent Class Analysis (LCA) to identify latent classes of social media users. The analysis uses variables capturing Likert-scale measures of platform-specific social media use (e.g., Facebook, Instagram, LinkedIn, Twitter, YouTube, Snapchat, Telegram, WhatsApp, Twitch, TikTok, Discord). Subsequently, we re-plot Kaplan–Meier curves to assess whether transition patterns differ across the identified user classes. In the final stage, we infer causal relationships by using platform-specific Likert-scale measures of social media use as explanatory variables and employing parametric g-formula for each transitional event. This approach allows us to flexibly estimate causal effects while accounting for confounding factors, capturing complex dependencies, and simulating counterfactual scenarios under different social media use levels (Hernan, 2024).

Preliminary Results and Future Steps

Figure 1 presents the Kaplan–Meier survival analysis. Figure 1 reveals differences in the timing of key life-course transitions between social media users and non-users. For the transition out of higher education, non-users and users differ significantly, with social media users completing education earlier ($\chi^2 = 25.9$, $p < 0.001$). Similarly, for the transition to work, users tend to get a job earlier than non-users, and this difference is statistically significant ($\chi^2 = 6.8$, $p = 0.009$). In contrast, the timing of transition to cohabitation does not differ significantly between the two groups ($\chi^2 = 1.1$, $p = 0.3$). For the transition to independent living, there is a suggestive but not statistically significant difference, with social media users leaving slightly earlier ($\chi^2 = 3.3$, $p = 0.07$). Finally, for the transition to the first child, non-users appear to have children slightly earlier, although this difference is not statistically significant ($\chi^2 = 2.9$, $p = 0.09$).

Table 1 presents the results from generalized linear models using different types of social media use as predictors, and controlling for age, gender, and ethnicity. The results highlight associations between social media platform use and markers of the transition into adulthood. Notably, LinkedIn is strongly associated with higher education completion and first job attainment, while Instagram and Facebook are linked to independent living, potentially reflecting their role in housing searches. Although these results do not account for selection, reverse causality, or other relevant covariates, they provide preliminary evidence supporting a foundational assessment of the causal relationship between social media use and life course outcomes in future stages.

Finally, in **Table 2** we present the pooled Latent Class Analysis results, giving the class groups for future analyses. The model identifies four emerging classes: Social Networkers, Light users, Career oriented users, and Moderate users. *Social networkers* have particularly high uses of classical social media platforms (Instagram, Facebook, Whatsapp), while *light users* have low to zero use of any social media platform. *Career oriented* users mainly use Linkedin and Twitter, and *moderate users* have average use of all the platforms.

In the future, we will: (1) increase sample sizes by linking LISS to administrative data, allowing us to follow individuals over longer periods and improving the likelihood that they are included in the final sample; and (2) apply the parametric g-formula to assess the causal mechanisms linking social media use to transition into adulthood to capture the dynamic interplay between social media use and life course transitions, enabling more robust causal inference.

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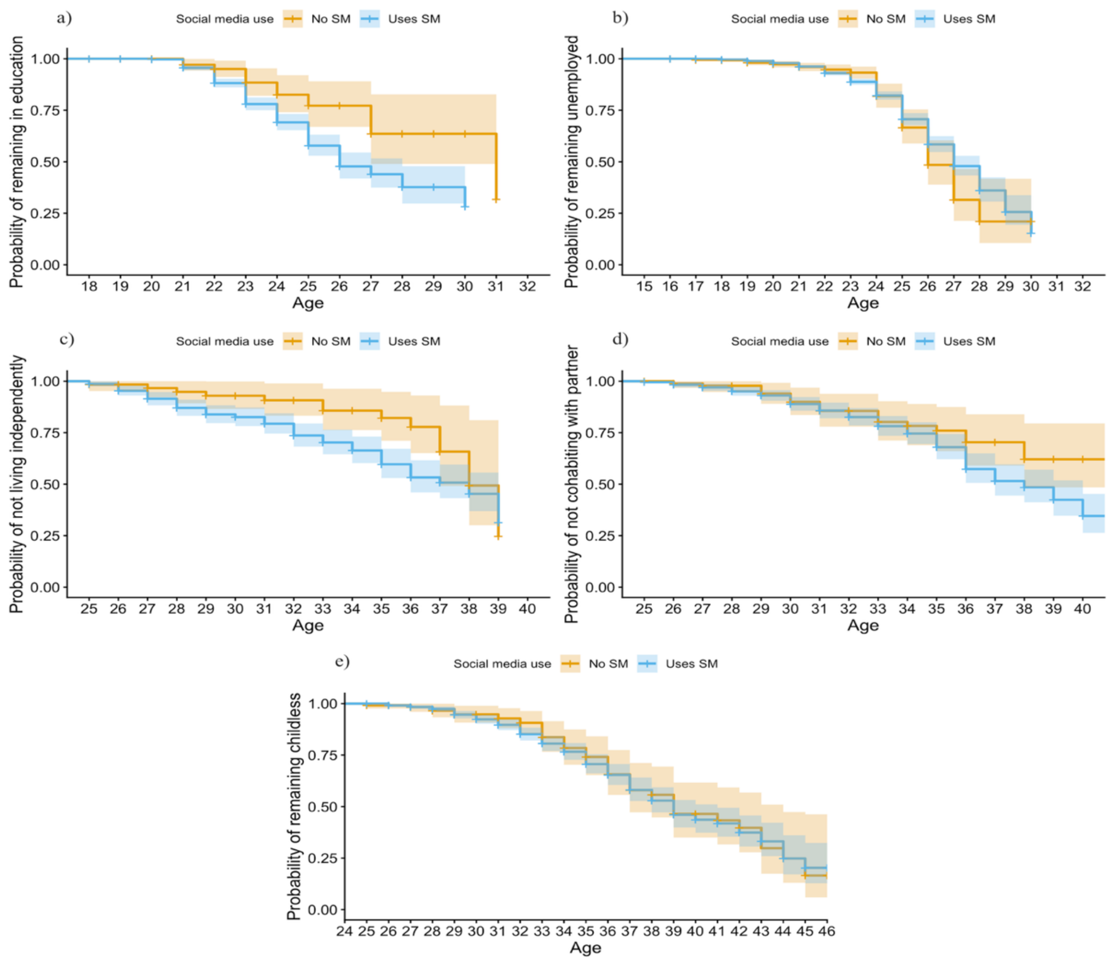
Figure 1. Kaplan-Meier plots for five markers of transition to adulthood



Note: In panels (a), (d), and (e), the reported probabilities are conditional on attending tertiary education (panel a), and, for panels (d) and (e), on being part of the subsample of individuals who cohabit or have children at a given point in time, respectively.

Table 1. Associations between social media platforms' use and transitional markers

	Higher education	First Job	Independent living	Cohabitation	Childbearing
Instagram use	-0.252**	-0.008	-0.133***	-0.132	-0.046
	(0.092)	(0.059)	(0.039)	(0.114)	(0.076)
Facebook use	0.225***	0.081*	0.090**	0.069	0.106*
	(0.051)	(0.033)	(0.034)	(0.066)	(0.050)
Twitter use	0.118+	0.081+	0.127*	0.029	0.037
	(0.068)	(0.045)	(0.049)	(0.088)	(0.069)
LinkedIn use	-0.443***	-0.246***	0.029	-0.012	-0.099
	(0.054)	(0.037)	(0.039)	(0.074)	(0.064)
Snapchat use	0.038	-0.062	0.114*	-0.087	0.014
	(0.072)	(0.052)	(0.050)	(0.115)	(0.105)
WhatsApp use	-0.094	0.185*	0.111+	0.672+	0.166
	(0.166)	(0.088)	(0.059)	(0.345)	(0.199)
TikTok use	-0.132*	-0.140***	-0.041	-0.099	-0.140
	(0.054)	(0.037)	(0.048)	(0.117)	(0.095)
Discord use	0.303	0.066	-0.724***	13.492	-0.095
	(0.218)	(0.127)	(0.181)	(535.411)	(0.369)
Twitch use	-0.326	-0.226	0.661***	-13.169	0.098
	(0.257)	(0.162)	(0.192)	(535.412)	(0.610)
Telegram use	-0.232	0.033	0.084	-0.299	-0.007
	(0.165)	(0.118)	(0.072)	(0.914)	(0.508)
Age	0.492***	0.365***	-0.043***	0.115***	0.100***
	(0.034)	(0.019)	(0.013)	(0.024)	(0.017)
Gender	0.648***	0.291**	0.393***	0.375+	0.257
	(0.162)	(0.103)	(0.111)	(0.220)	(0.176)
Ethnicity	-0.003*	-0.004***	0.005***	0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Num. Obs.	2872	5602	2602	522	832
AIC	1306.6	2898.7	3000.2	619.5	962.7
BIC	1390.1	2991.6	3082.3	679.1	1028.9
Log Likelihood	-639.317	-1435.372	-1486.078	-295.767	-467.359
RMSE	0.26	0.28	0.44	0.44	0.44

+ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 2: Average characteristics of the classes estimated through LCA

Characteristic	Social Networkers	Career Oriented	Moderate Users	Light Users
Age (years)	28.06	28.92	28.76	32.16
Gender (1 = male, 2 = female, 3 = Other)	1.66	1.41	1.45	1.47
Urbanicity	2.64	2.59	2.56	2.74
Educational level (1–7)	4.48	4.65	4.71	4.54
Income (Euro)	1,750	2,297	2,158	2,142
Facebook Use	2.12	2.11	2.10	3.40
Snapchat Use	3.25	3.71	3.47	4.93
Instagram Use	1.76	2.10	2.09	4.72
Twitter Use	4.79	2.01	3.32	4.88
LinkedIn Use	4.06	3.52	3.50	4.32
WhatsApp Use	1.13	1.20	1.15	1.63
Telegram Use	4.81	4.33	4.51	4.85
Twitch Use	4.90	4.53	4.65	4.94
TikTok Use	3.86	3.89	3.66	4.90
YouTube Use	4.79	2.01	3.31	4.88
Discord Use	4.73	4.07	4.27	4.84
N	3639	598	559	1838

Notes: Values represent class-specific means. Usage variables are coded 1 (Every day) to 5 (Never). Gender coded as 1 = male, 2 = female, 3 = Other. Urbanicity coded 1–5, with 1 = very urban, 5 = not urban. Educational level on a 1–7 scale.