Social Indicators Research
https://doi.org/10.1007/s11205-024-03320-z

ORIGINAL RESEARCH

Tackling Cyclicity in Causal Models with Cross-Sectional Data Using a Partial Least Squares Approach: Implications for the Sequential Model of Internet Appropriation

Giuseppe Lamberti[1] · **Jordi Lopez-Sintas**[1] · **Giuseppe Pandolfo**[2]

Accepted: 23 January 2024
© The Author(s) 2024

Abstract

Working with SEM and cross-sectional data, and depending on the studied phenomenon, assuming an acyclic model may mean that we obtain only a partial view of the mechanisms that explain causal relationships between a set of theoretical constructs, given that variables are treated as antecedents and consequences. Our two-step approach allows researchers to identify and measure cyclic effects when working with cross-sectional data and a PLS modelling algorithm. Using the resources and appropriation theory and the sequential model of internet appropriation, we demonstrate the importance of considering cyclic effects. Our results show that opportunities for physical access followed by digital skills acquisition enhance internet usage (acyclic effects), but also that internet usage intensity, in reverse, reinforces both digital skills and physical access (cyclic effects), supporting Norris (Digital divide: civic engagement, information poverty, and the internet worldwide. Cambridge University Press, Cambridge, 2001) social stratification hypothesis regarding future evolution of the digital divide.

Keywords Cyclic effects · PLS-SEM · Digital divide · Internet appropriation · Digital skills · RA theory

✉ Giuseppe Lamberti
giuseppe.lamberti@unina.it

Jordi Lopez-Sintas
jordi.lopez@uab.cat

Giuseppe Pandolfo
giuseppe.pandalfo@unina.it

[1] Department of Business, School of Economics and Business, Universitat Autònoma de Barcelona, Campus UAB, B Building, Room B1/118, 08193 Bellaterra, Barcelona, Spain

[2] Department of Economics and Statistics, University of Naples Federico II, Room C5, Via Cintia, 21, 80126 Naples, Italy

Published online: 20 April 2024

1 Introduction

Structural Equation Modelling (SEM) is a commonly applied multivariate approach to examining complex systems of variables (Hair et al., 2022). According to Wold (1982), the two most essential prerequisites for SEM are (1) that a cause-effect relationship is hypothesized between variables, and (2) that most variables are not directly observable (i.e., they are latent) and so must be measured using a specific set of indicators.

The available literature outlines various approaches that can be used to estimate SEM. The classic approach is the well-known covariance-based SEM (Ullman & Bentler, 2012), which considers a latent variable to be a common factor that explains the co-variation of its own set of indicators (Sarstedt et al., 2016). This approach typically relies on stringent assumptions about distributions and sample size. Partial Least Squares (PLS) SEM is an alternative approach (Sarstedt et al., 2016) that approximates latent variables as a proxy (i.e., a linear combination of indicators) and aims to maximize the explained variance of both the indicators and dependent constructs.

In almost all cases, SEM applications are conditioned by a critical hypothesis that Hyttinen et al. (2012) define as the "acyclic" hypothesis, which assumes that variables are antecedents or consequences, and that the causal relationship between variables can be estimated considering a specific time interval. In other words, the acyclic hypothesis operates in SEM when a one-way sequential effect regulates the relationship between variables. However, as indicated by Hyttinen et al. (2012), there are several situations in which variables influence each other in a cyclic manner, which means that we cannot assume acyclicity if we want to measure the complete structure of causal relationships between variables. Thus, being able to measure cyclicity in SEM remains of fundamental importance.

In the sociology field, one scenario deserving of attention regarding acyclic and cyclic effects is the elucidation of social disparities in Internet adoption and usage. The Resources and Appropriation (RA) theory, as articulated by van Dijk (2002), van Deursen and van Dijk (2015), and van Dijk (2020), delineates the production and reproduction of social inequalities in Internet appropriation, commonly referred to as the digital divide, which, according to this theory, arises from four key constructs: attitude (reasons and motivations for Internet use), access (physical availability of digital devices and connections), skills (digital proficiency), and usage (how the Internet is actually used). The RA theory and the associated Internet appropriation model assumes that those four constructs function sequentially, i.e., attitude influences access, which influences skills, which, in turn, influences usage. However, it is intuitive that usage also exerts a reverse influence on attitude, access, and skills; moreover, the fact that the temporal dimension is not considered means that a static snapshot is offered of a moment in time.

In proposing a new SEM algorithm that takes into account the time dimension, Asparouhov et al. (2018) and Drton et al. (2019) resolved the problem of cyclicity in SEM, although their proposal was based on longitudinal data, i.e., the same set of variables measured at different times. Since this kind of data is not usually available in SEM studies, most analyses are cross-sectional. Indeed, how to measure cyclic effect in SEM when working with cross-sectional data remains an open research question.

To close this research gap, we propose a two-step approach to measuring cyclic effects when working with cross-sectional data using the PLS algorithm. Our approach is based on estimating a classical PLS-SEM model and then use the resulting dependent variable scores to estimate the cyclic effects. Our approach applies the same philosophy as used for hierarchical models with higher-order constructs in PLS-SEM (Becker et al., 2012;

Crocetta et al., 2021; Sarstedt et al., 2019). Hierarchical models use multidimensional constructs that exist at a higher level of abstraction but are quantified using lower-order subconstruct latent scores as proxies.

In summary, this article aims to offer a methodological contribution to further developing PLS-SEM so as to measure a cyclic feedback loop. It also makes a sociological contribution in extending the sequential model of Internet appropriation (van Deursen & van Dijk, 2015) to account for possible cyclic effects operating on the digital divide.

Our article is laid out as follows. First, we introduce the issue of cyclicity through an example from the sociology field. We concisely overview the digital divide concept, the RA theory, and the sequential Internet appropriation model, underlining the significance of accounting for cyclic effects for our understanding of the social mechanisms influencing Internet appropriation (Sect. 2). We next provide a brief introduction to PLS-SEM and outline our two-step approach to estimating cyclic effects in the PLS-SEM context (Sect. 3). Using data from a Eurostat Information and Communication Technology (ICT) usage survey, we demonstrate how we apply this approach to estimating cyclic effects in the Internet appropriation model (Sect. 4). Finally, we discuss the methodological and substantive contributions of our research (Sects. 5 and 6).

2 Conceptual Background

2.1 RA Theory and the Digital Divide

The digital divide is not just a metaphor, but points to a social problem: unequal access to and use of the ICTs. Nor is the digital divide a theory, as underlined by van Dijk (2002), as it has successfully directed attention towards social, political, and academic debates (Attewell, 2001). While the digital divide initially referred to unequal access to the ICTs, the evidence is that the issue is more complex than mere access (Norris, 2001). Unequal access to the ICTs nowadays is understood to be just a starting point for unequal endowment in devices, which also encompasses unequal attitudes, skills, and usage. However, the digital divide has several facets that need further explanation: (1) the theoretical relationships between unequal layers in the sequential process that culminate in unequal digital benefits (van Deursen & van Dijk, 2015; van Dijk, 2002, 2005, 2012, 2020), (2) the evolution of the digital divide (Norris, 2001; van Dijk, 2012), and (3) the unequal social distribution of the digital divide (van Deursen & van Dijk, 2014, 2015).

The digital divide, coined as a term by the US National Telecommunications and Information Administration, initially described the uneven distribution of computers among low-income groups, minorities, women, and the elderly (Norris, 2001; Parsons & Hick, 2008). That divide is now commonly referred to as the first digital divide (Attewell, 2001), because, despite policies implemented to address what was essentially an access gap, subsequent research has revealed that a more enduring Internet usage gap exists—referred to as the second digital divide—that is characterized by disparities in how people actually use the Internet (Attewell, 2001). Furthermore, attempts to understand the processes that generate the second divide have led to the identification of a third divide, reflecting the social and cultural advantages/disadvantages accruing to individuals with better/poorer digital skills (Hargittai, 2002; van Deursen & Helsper, 2015). This skills gap suggests that a better understanding of the digital divide requires a better understanding of digital divide levels and the links between them.

The RA theory posits a model of Internet appropriation that aims to elucidate the digital divide by establishing a sequential connection between attitude, physical access, digital skills, and usage. According to this theory, disparities in the advantages derived from Internet usage stem from an uneven societal distribution of those four constructs (as will be briefly elaborated in connection with our research findings described below). Table 1 summarizes definitions, effects, and literature references for each construct. For a complete review, see Lamberti et al., (2021, 2023), van Deursen and van Dijk (2015), and van Dijk (2020).

Our model, based on the model proposed by van Deursen and van Dijk (2015) and Lamberti et al., (2021, 2023), is illustrated in Fig. 1, includes three constructs: physical access (PA), digital skills (DS), and Internet usage (IU). Attitude (ATT) as an antecedent of PA was excluded, as our use of secondary data did not allow its consideration.

2.2 The Sequential Model: Cumulative and Cyclic

So far, we have described the constructs underpinning the sequential model of Internet appropriation that produce different digital divide levels. However, even though the causality model that explains the third digital divide (arising from social and cultural advantages/disadvantages) is sequential, the RA theory also indicates that the model is, additionally cumulative and recursive (van Dijk, 2002, 2006), and applies equally to older and newer media.

The sequential levels of the digital divide are cumulative in two ways. First, cumulative waves of innovation have led to desktop computers, the Internet, laptops, netbooks, tablets, smartphones, and many other spin-off devices. Network innovations further enhance devices, e.g., smartphone usefulness has been enhanced by the advent of 3G, 4G, and 5G data technologies. Devices differ in terms of cost, typically related to ease of use, operating systems, and the innovativeness of embedded technologies. The fact that more costly devices are faster, easier to use, and have better software ultimately affects what the individual can do and the derived benefits. Second (and related to this last point), individuals adopt new technologies at different temporal points (Norris, 2001; van Dijk, 2002, 2006) and speeds. If the adoption pattern of digital technologies were to follow Norris' normalization hypothesis (2001), which suggests that social differences could eventually fade away, all individuals would finally achieve the same level of adoption. However, evidence for Europe, as reported by Norris (2001), supports a social stratification thesis, i.e., the persistence of social differences reflected in the digital divide. Thus, society is stratified into privileged and underprivileged social groups that achieve different levels of adoption at varying times in line with their resources, and the outcome is a divergence in life chances and varying access to capital and resources and to privileged social positions.

The sequential model is also cyclic. With each new digital innovation, the adoption process starts again and runs concurrently with previous adoption processes, although skills, usage, and benefits may be fundamentally grounded in previous experiences. The fact that many innovations build on an earlier innovation makes it easier for people who have already adopted a technology to foresee the value of an enhancement. Those left behind will see their digital skills stagnate (i.e., the skill difference will be more significant in both absolute and relative terms), and they will not enjoy the social and economic benefits of the more advanced technology. The skills deficit, in turn, may reduce motivations to adopt a new digital innovation. Furthermore, each advance in digital devices typically combines with other complementary innovations that reinforce productivity, e.g., smartphones with

Table 1 Sequential model of Internet use construct: definitions, effects and references

Construct	Definition	Positive effect	References
Attitude (ATT)	Personal motivations to use digital technologies	Access, digital skills, and usage	van Deursen and van Dijk (2015), Venkatesh et al. (2003)
Physical access (PA)	Opportunity to connect to the Internet, via devices (desktops, laptops, tablets, smartphones, gaming consoles, interactive television)	Digital skills and usage	Hargittai (2002), Kuhlemeier and Hemker (2007), Mossberger et al. (2012), van Deursen and van Dijk (2015, 2019), Zillien and Hargittai (2009)
Digital skills (DS)	Capacity to use the Internet	Usage	Ferrari (2012), Hargittai (2002), Hargittai et al. (2019), Hargittai and Shafer (2006), van Deursen and Mossberger (2018), van Deursen and van Dijk (2014, 2015), van Dijk and Hacker (2003)
Internet usage (IU)	Quantity and diversity of online activities		Blank and Groselj (2014), Hargittai and Hinnant (2008), van Deursen and van Dijk (2014)

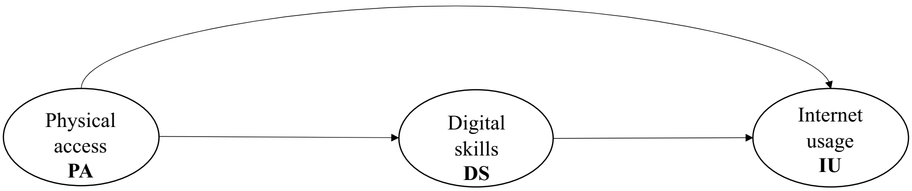


Fig. 1 The sequential model of Internet appropriation

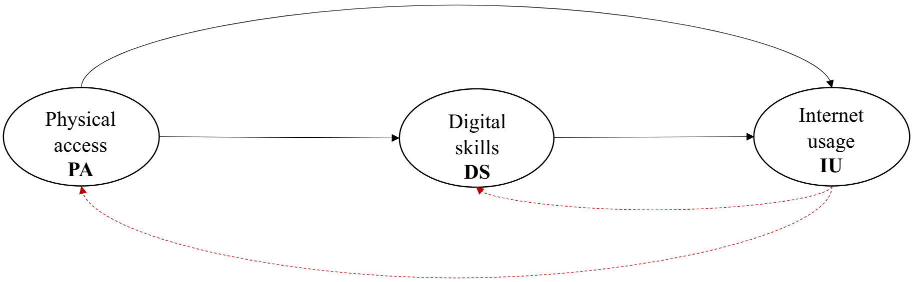


Fig. 2 The cyclic model of Internet appropriation

advanced printers, television sets with Internet connections, laptops with long-lasting batteries, and smartphones sharing access to local and global computer networks, shared broadband access at home or in the office, and the new WIFI mesh technologies.

The cumulative and cyclic properties of the model are shown in Fig. 2 (red lines), which depicts what we call the cyclic model of Internet appropriation. The cumulative and recursive properties suggest that the sequential effect of the different digital divides is underestimated when we use cross-sectional data because cyclic effects are not reflected in the sequential model.

3 Method

3.1 PLS-SEM

PLS-SEM (Esposito Vinzi et al., 2010; Hair et al., 2022; Tenenhaus et al., 2005; Wold, 1985) connects a set of observed variables (i.e., indicators or manifest variables) with constructs through a system of linear relationships (Hair et al., 2022) that are simultaneously quantified by applying a set of sequential multiple linear regressions. Following Sarstedt et al. (2016), PLS-SEM is a composite approach to SEM, meaning that all latent variables are approximated using a linear combination of indicators. Figure 3 depicts the model specification considering a simple model where there are three LVs, each related to a block of three MVs. Computed are two models: an outer model that relates manifest variables (MVs) to constructs as latent variables (LVs), and an inner model that reflects the strength and direction of relationships between the LVs.

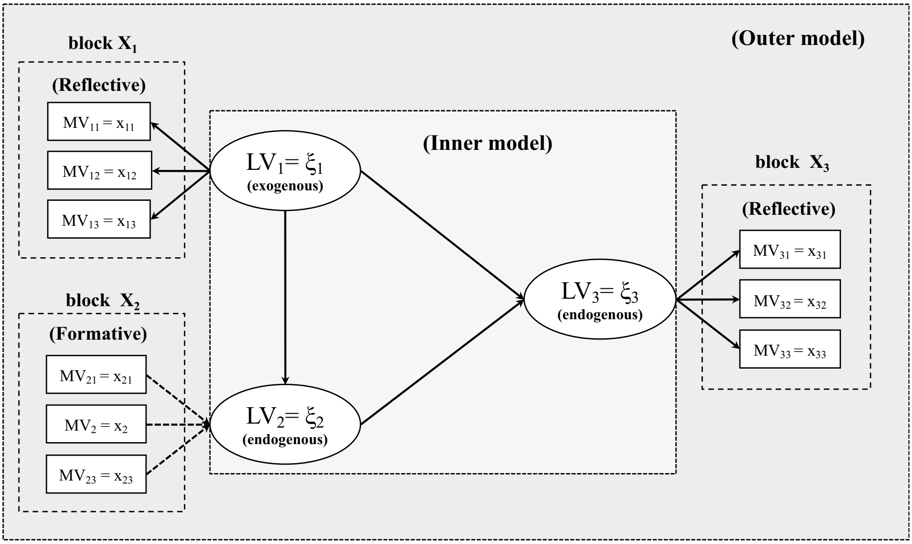


Fig. 3 PLS-SEM model specifications

According to Sarstedt et al. (2016), in the outer model, the relationship between LVs and their indicators can be conceptualized using reflective and formative approaches. The relationship is reflective (blocks 1 and 3, Fig. 3) when it is hypothesized that an LV causes the observed association with an indicator, while the relationship is formative (block 2, Fig. 3) when an LV is generated by a linear combination of indicators (in the form of a scale). Reflective, but not formative, relationships must be highly correlated as each indicator describes a different aspect of the LV.

Referring to Fig. 3, let us assume that we have P indicators that are observed on N units, $(i=1,\ldots, n,\ldots, N)$, then the data x_{npk} are collected in a partitioned matrix $X=[X_1,\ldots, X_k,\ldots,X_K]$ where x_{pk}, with $p=1,\ldots, p_k$, and $\sum_{k=1}^{K} p_k = P$ is an indicator belonging to the *k-th* block X_k. We also assume that an LV ξ_k is associated with each block X_k.

Following Tenenhaus et al. (2005) and Wold (1982), the reflective blocks X_1 and X_3 and the formative block X_2 in the outer model are formalized in Eqs. (1) and (2), respectively:

$$\mathrm{x}_{pk} = \lambda_{pk}\xi_k + \varepsilon_{pk} \tag{1}$$

$$\xi_k = \sum_{k} \pi_{pk}\mathrm{x}_{pk}, \tag{2}$$

where in the reflective case, λ_{pk} is the loading coefficient that captures the effect of ξ_k on $^{x}{}_{pk}$, while in the formative case, π_{pk} represents the weight of the linear combination associated with the indicator $^{x}{}_{pk}$, and $^{\varepsilon}{}_{pk}$ is the measurement error variable.

Finally, a generic dependent LV is linked to the corresponding explanatory LVs by the following equation:

$$\xi_k = \beta_{kk'}\xi_{k'} + \zeta_k, \tag{3}$$

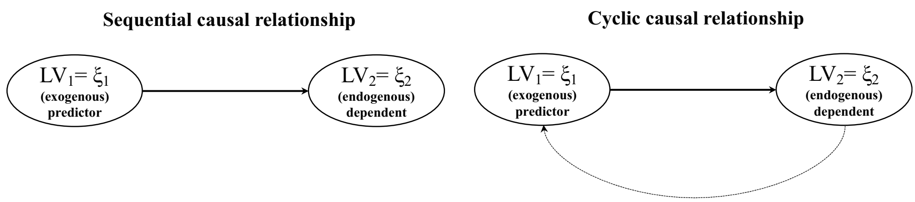


Fig. 4 Simple causality path model

where $\beta_{kk'}$ is what is known as a path coefficient, which captures the effects of the predictor LV $\xi_{k'}$ on the dependent LV ξ_k, and where ζ_k is the inner residual variable.

Model parameters are estimated in PLS-SEM using a four-step iterative algorithm that includes: (1) an external approximation, (2) an internal approximation, (3) weight updating, and (4) a convergence check (see Hair et al. (2022) and Tenenhaus et al. (2005) for a detailed description of each step).

Concerning validation, several tests can assess the quality of the outer model. For instance, Cronbach's α and Dillon-Goldstein's ρ, which measure how well a block of MVs measures the corresponding LV support researchers in their assessment of construct reliability. Average Variance Extracted (AVE), which measures the amount of MV variance captured by each LV, depicts convergence validity. Composite Reliability (Cronbach's α and Dillon-Goldstein's ρ), as put forward by Dijkstra (Dijkstra & Henseler, 2015), is suitable for reflective LVs (e.g., if mimicked by PLS-SEM) but less useful than components (as estimated by PLS-SEM).

As for the inner model, this is validated by analysing the length and significance of the path coefficients and using R^2. Further details and a comprehensive list of possible tests are available in Espostio Vinzi et al. (2010), Hair et al. (2022).

3.2 Cyclic Effects in PLS-SEM

Consider a simple model with two LVs, one exogenous (i.e., predictive (ξ_1)) and the other endogenous (i.e., dependent (ξ_2)), reflecting antecedents and consequences. Note that, for the sake of simplicity, we do not differentiate between exogenous and endogenous in the notation. Under the classical causal model paradigm, we have a causal relationship between ξ_1 and ξ_2 when ξ_1 affects ξ_2 ($\xi_1 \rightarrow \xi_2$); this effect is sequential, as we can establish a temporal order between the two LVs, such that ξ_1 is antecedent to ξ_2 (Fig. 4, left). Another situation is when ξ_1 affects ξ_2 and when ξ_2 also affects ξ_1 ($\xi_1 \rightleftarrows \xi_2$), i.e., ξ_1 and ξ_2 are involved in a feedback loop; in this case, the influence is cyclic (Fig. 4, right).

Considering the sequential model of Internet appropriation and the relationship between the constructs, we can intuitively infer a sequential effect: if people have opportunities to physically access the Internet (PA), they will develop better digital skills (DS), and this will increase their usage (IU). However, just as intuitively, we can also infer a cyclic effect: more use of the Internet (IU) will result in more physical access (PA) and better digital skills (DS).

In PLS-SEM (as mentioned earlier), we face the problem of estimating the cyclic effect when working with cross-sectional data: we do not have the same indicators measured for the same individuals at different time points. Indeed, we can say that measurement of the variables at another time point is latent. However, let us assume that cyclic effects exist (as

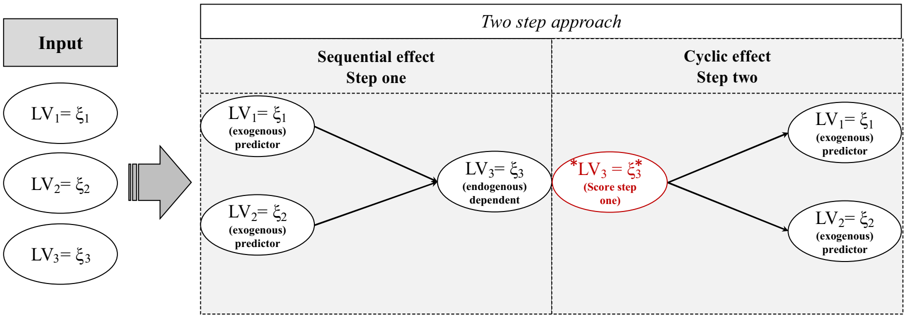


Fig. 5 Two-step approach to estimating cyclic effects

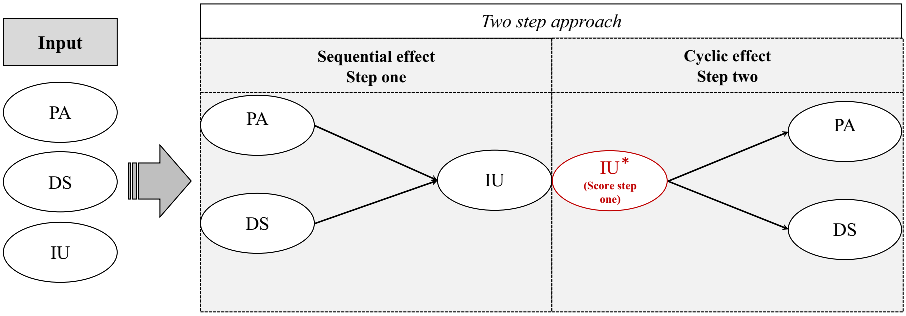


Fig. 6 Two-step approach to estimating cyclic effects in Internet appropriation

intuited above in relation to Internet appropriation and its constructs) and that we want to map the entire relationship structure. In this case, we account for any cyclic effect by using available variables to generate a proxy of variables measured at different time points.

3.3 The Proposed Two-Step Approach

Our proposal for estimating cyclic effects for cross-sectional data involves two steps. Let us to consider a simple case with three LVs (ξ_1, ξ_2, ξ_3) as depicted in Fig. 5. Its generalization into a more complex case is straightforward. First, to identify sequentiality in the LVs, we estimate the model applying the classical PLS-SEM procedure and calculating the coefficients and dependent LV scores. In our example, since ξ_1 and ξ_2 are predictors of ξ_3, we determine the path coefficients $\beta_{\xi_1\xi_3}$ and $\beta_{\xi_2\xi_3}$ and the score for ξ_3. Second, we estimate cyclic effects in a separate model where the dependent LV (ξ_3) is now used to predict the antecedent variables (ξ_1 and ξ_2) using, instead of the original LV indicators, the dependent LV score (ξ_3^*).

Application to Internet appropriation and the PA, DS, and IU constructs (Fig. 6) is as follows: in the first model, sequentiality is established for PA, DS, and IU, and path coefficients and scores are calculated; and in the second model, IU is established as an antecedent of both PA and DS, and the IU score (IU*) obtained in the first model now yields the new path coefficients that quantify the cyclic effects.

Determining cyclic causality requires not only quantifying effects (length and significance) but also determining the relative significance of cyclic effects versus sequential effects: if the cyclic effect is significantly greater than the sequential effect, we can point to a reinforcement effect. Therefore, considering the sequential model of Internet appropriation, if the cyclic effect of IU on PA and DS is significantly greater than the sequential effect, then we can assume that the sequential effect of PA and DS on IU reinforces the effect of IU on PA and DS.

We used an adaptation of the parametric test introduced by Keil et al. (2000), which assesses the significance of the effect of categorical variables on a path coefficient estimated through PLS-SEM.[1] Following Keil et al. (2000), and considering a simple model with two LVs (Fig. 4, right), we compared significant differences between sequential and cyclic effects (SE and CE in the equations below) by comparing differences between two coefficients and using the bootstrapping procedure to estimate the standard error. In the adapted parametric test, the null hypothesis is that there is no difference between SE and CE effects (i.e., $H_{0:}\ \beta_{SE} = \beta_{CE}$), while the alternative hypothesis is that the CE effect is significantly greater than the SE effect (i.e., H_1: $\beta_{SE} > \beta_{CE}$). The null hypothesis is tested, and *df* is determined as follows:

$$t = \frac{|\beta_{SE} - \beta_{CE}|}{\sqrt{\frac{(n-1)}{n}\left(\sigma^2_{\beta_{SF}} + \sigma^2_{\beta_{CE}}\right)}}. \tag{4}$$

$$df = \sqrt{\frac{\left(\frac{(n-1)}{n}(\sigma^2_{\beta_{SE}} + \sigma^2_{\beta_{CE}})\right)^2}{\frac{(n-1)}{n^2}\left(\sigma^4_{\beta_{SE}} + \sigma^4_{\beta_{CE}}\right)}}. \tag{5}$$

4 Illustration: Accounting for the Cyclic Effect

In this section we show how to estimate the cyclic effect by applying the two-step approach to the sequential model of Internet appropriation. Below we briefly present our data and describe the results of our analysis. Data, measurements, and model were based on the analysis proposed by Lamberti et al. (2021). The analysis was performed in R, using the ‘FactoMineR’ package (Lê et al., 2008) to run the multiple correspondence analysis (MCA) and to operationalize the PA construct, the ‘plspm’ package (Bertrand et al., 2023) to estimate the PLS-SEM model and the cyclic effects. The authors, implemented the parametric test.

[1] The parametric test is based on a bootstrap resampling procedure to evaluate coefficient differences. The bootstrap procedure estimates the standard errors of the path coefficients estimated for each group defined by the categorical variable levels. The difference between coefficients is then tested using a t-statistic (for details, see Keil et al. (2000)).

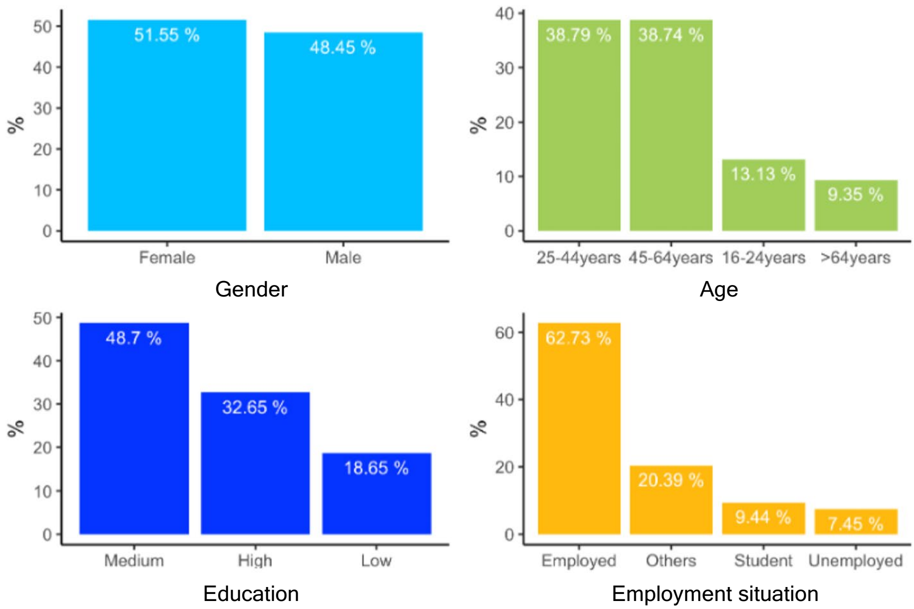


Fig. 7 Sample characteristics

4.1 Data and Measurements

We obtained representative data on ICT usage in 2016 from a Eurostat EU27 + UK survey. The sample consisted of 151,660 individuals aged over 15 years who had used the Internet in the three previous months. Figure 7 depicts the sample demographics, showing that slightly over half were female, approximately three quarters were aged 25–64 years, about a third had a high level of education, and around two thirds were employed.

Measurement of the RA theory indicators (PA, DS, and IU) is briefly summarized below (full details are available in Appendix 1).

PA was measured in terms of a yes/no response regarding the use of six device types (personal computer, portable computer or netbook, tablet, mobile phone or smartphone, other mobile device (e.g., e-reader, smartwatch), and smart TV). Due to the dichotomous nature of the indicators, PA was operationalized through MCA (Greenacre & Blasius, 2006), with the coordinates for the first dimension reflecting PA intensity. Figure 8, which depicts the two first MCA dimensions, shows variables coloured by contribution (darker shades reflect greater contributions). The first dimension, reflecting PA intensity and accounting for more than 76% of the total inertia, contrasts non-use and use of particular devices (left- and right-hand side of the plot, respectively), showing that smartphones and tablets make the greatest contribution to this dimension.

DS was measured in terms of four abilities labelled as information skills (use of communication applications, networks and digital devices to access and manage information), communication skills (use of technology to communicate with others), problem-solving skills (use of technology for to resolve tasks), and software skills (use and knowledge of software). Self-reported skill levels, quantified using a four-point Likert scale, ranged from 1 (no skills) to 4 (advanced skills).

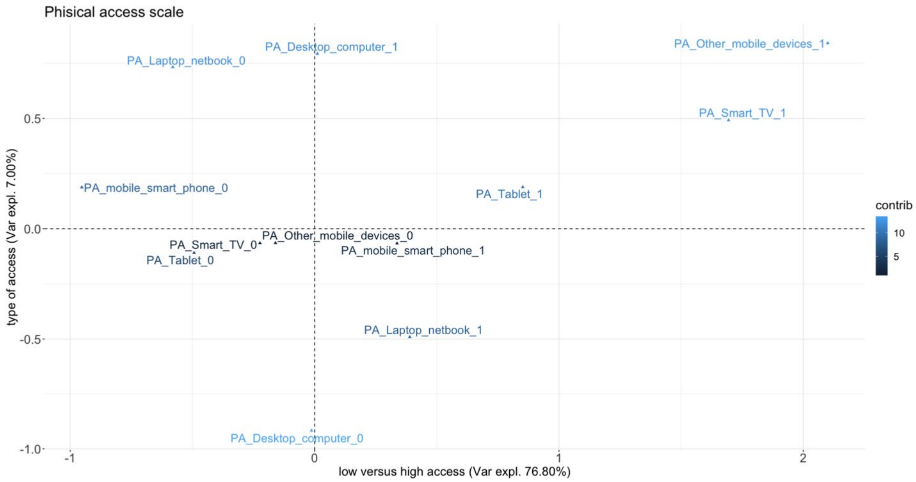


Fig. 8 MCA factorial map of physical access intensity

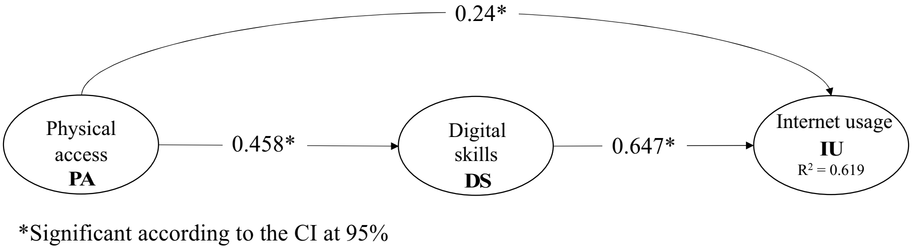


Fig. 9 Sequential model estimation

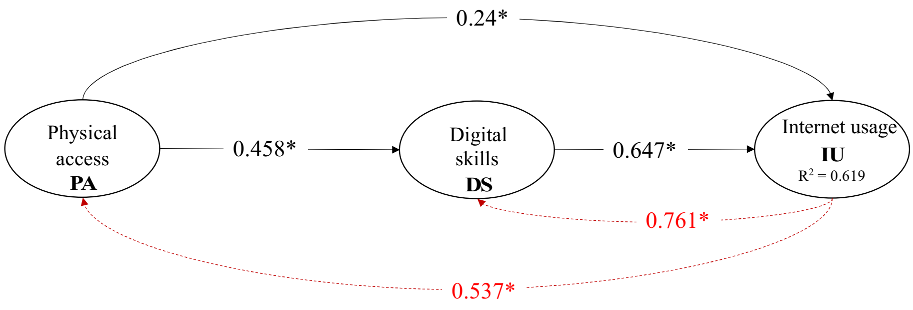
Finally, IU was measured in terms of online activities (including emailing, reading news, playing games, listening to music, managing a website, running a business, etc.), grouped into four categories (following van Deursen and van Dijk (2014) and Blank and Groselj (2014)) labelled social interaction, information-seeking, leisure, and commercial transactions. Self-reported activity levels were quantified using a four-point Likert scale, ranging from 1 (not used at all) to 4 (very frequently used).

4.2 Results

4.2.1 Sequential Model Results

Since PA was operationalized using the MCA first dimension, i.e., a single item scale, no further validation was required during analysis of the measurement model.[2] Regarding DS and IU, we adopted a reflective approach, assuming that each acted as an antecedent of their respective indicators. Validation was based on examining the reliability indices

[2] Note that MCA scales are considered optimal scales, in line with Greenacre and Blasius (2006).



*Significant according to the CI at 95%

Fig. 10 Cyclic model estimation

Table 2 Parametric test results

Effects	SE	CE	Abs (diff.)	t-statistic	p-value
PA ⇄ IU	0.240	0.537	0.297	126.810	0.002
DS ⇄ IU	0.647	0.761	0.114	75.580	0.004

SE, sequential effect; CE, cyclic effect

following Esposito Vinzi et al. (2010) and Hair et al. (2022). Results, reported in Appendix 2, are consistent with evidence reported by Lamberti et al., (2021, 2023).

Evidence supporting sequential causality is depicted in Fig. 9, which shows the path coefficient and R^2 results for the inner model (significance according to a 95% confidence interval (CI) is indicated by asterisks). Our results suggest that PA strongly influences DS ($\beta = 0.458$), and less strongly affects IU ($\beta = 0.240$), while the most significant influence on IU is DS ($\beta = 0.647$).

4.2.2 Cyclic Model Results

Figure 9 depicts a partial representation of reality, illustrating the sequential effects of PA on DS and IU, and of DS on IU. Indeed, as shown in Fig. 10, the influence of the constructs also exhibits a cyclical pattern (highlighted by lines and coefficients in red). Specifically, IU significantly and reciprocally impacts both PA ($\beta = 0.537$) and DS ($\beta = 0.761$).

Table 2 summarizes the parametric test results for PA, DS, and IU, comparing the significance of the cyclic effect with that of the sequential effect. Reported, in order, for each pair of associated constructs (PA and IU and DS and IU), are the sequential effect (SE) the cyclic effect (CE), their absolute value differences, and the corresponding t-statistics and p-values. The findings confirm the presence of a reinforcement effect: the cyclic coefficients (IU on PA, and IU on DS) are notably higher than the sequential coefficients (PA on IU, and DS on IU).

5 Discussion

We introduce a novel, easily implementable, and straightforward two-step approach, based on using the PLS algorithm, to addressing cyclic effects in SEM when working with cross-sectional data. The method consists of first estimating the classical PLS-SEM model, and then using the resulting scores for the dependent variable to determine cyclic effects. A distinctive feature of this method is its applicability to cross-sectional datasets that generally consist only of data collected at a specific moment of time.

While the sequential model of Internet appropriation, as proposed by the RA theory, provides valuable insights into the digital divide, its acyclic assumption offers only a partial understanding of the underlying social mechanisms that regulate Internet appropriation and usage.

To demonstrate the significance of accounting for cyclic effects, we built an adapted version of the sequential model proposed by van Deursen and van Dijk (2015), using secondary ICT data from Eurostat and including three constructs: physical access, digital skills, and Internet usage. We analysed the sequential causality between those constructs so as to determine if, how, and to what extent PA and DS affect IU. Our exploration of effects yielded results consistent with previous research (Hargittai, 2002; Lamberti et al., 2021; van Deursen & Helsper, 2015), in that it highlights that PA plays a crucial role in DS but has a comparatively lesser impact on IU, which, in turn, is substantially influenced by DS.

Importantly, we identify cyclic effects that reveal that IU positively reinforces both PA and DS.

5.1 Methodological Contribution

Our approach makes an important methodological contribution, as it represents a first endeavour to address cyclicity within causal models using PLS-SEM and cross-sectional data. Our two-step approach represents an advance in terms of probing causal relationships between latent variables that encompass both acyclic and cyclic dynamics. This contribution is particularly significant in view of the fact that longitudinal datasets for the same group of observations are typically less accessible than their cross-sectional counterparts.

5.2 Sociological Contribution

From a sociological perspective, our methodology can potentially enhance studies of Internet appropriation. Compared to the sequential model of Internet appropriation (Lamberti et al., 2021, 2023; van Deursen & van Dijk, 2015), the cyclic model offers a more comprehensive understanding of the complex interplay between the social mechanisms underlying Internet appropriation. Notably, our findings align with Norris' social stratification thesis (2001), in revealing that not only is physical access instrumental for digital skills and that both exert influence on Internet usage, but also that Internet usage exerts a positive impact on both physical access and digital skills.

5.3 Limitations

Our approach is not without limitations. First, the estimated coefficients for the cyclic effects are merely a proxy for the real coefficients, given that we use the same set of variables for both the acyclic and cyclic effects. This limitation originates in the fact that we use cross-sectional data and so do not have same variables measured at different moments in time. Second, using the same set of variables to estimate acyclic and cyclic effects produces a bias in coefficient estimates, as cyclic effects depend on the indirect predictor variable effects on the dependent variable (in our case, PA and DS on IU). Thus, since we use PA and DS to estimate IU, and then use the IU score to estimate the return effect on PA and DS, we can expect the cyclic effect to be higher than in reality. However, this bias can theoretically be justified if we assume, based on intuition, that variables reciprocally influence each other. Third, this method can only be applied when there is at least one intermediate LV in the model (in our case, DS), i.e., cyclic effects cannot be estimated for just two constructs, but needs at least three. This limitation is due to how parameters are estimated in PLS-SEM. The path coefficients, in this particular case, correspond to the correlation coefficient; hence, if we only considered DS and IU as variables in the sequential model, we would obtain the same correlation coefficient as an estimate of both acyclic and cyclic effects. A final limitation is related to our use of secondary data, as it meant that we could not consider attitude as an antecedent of physical access, as posited by the RA theory, and also that scale measurement may have been affected by the fact that the available indicators were not as rich as the indicators obtained from surveys designed specifically to test a particular theory, as done by van Deursen and van Dijk (2015).

6 Conclusion and Further Research

When employing SEM with cross-sectional data, the assumption of an acyclic model may result in only a partial understanding of the mechanisms governing causal relationships among a set of theoretical constructs. This is because variables are treated solely as antecedents or consequences. Our two-step approach empowers researchers to discern and quantify cyclic effects when working with cross-sectional data utilizing a PLS modelling algorithm.

We underscore the significance of accounting for cyclic effects through the lens of RA theory and the sequential model of Internet appropriation. Our findings reveal that initial opportunities for physical access, followed by the acquisition of digital skills, contribute to heightened Internet usage (acyclic effects). We also establish that the intensity of Internet usage, in turn, bolsters both digital skills and physical access (cyclic effects), lending support to Norris' (2001) social stratification hypothesis regarding future evolution of the digital divide.

Looking ahead, in our ongoing research, we aim to delve deeper into the predictive capabilities of cyclic effects. This will involve comparing acyclic and cyclic models using metrics such as the Bayesian Information Criterion (BIC) (Sharma et al., 2021) and the Cross-Validated Predictive Ability Test (CVPAT) (Liengaard et al., 2021; Sharma et al., 2023).

Appendix

Appendix 1: Constructs Definition and Operationalization

For each construct, we provide the definition, the indicators used to measure it, an explanation of how it was operationalized, references, and a comparison with the construct employed in the van Deursen and van Dijk (2015) model.

Construct	Definition	Items	Operationalization	References	van Deursen and van Dijk (2015) model
PA	Device used to access the Internet	*Which of the listed devices have you used for Internet access?* personal computer, portable computer or netbook, tablet device, mobile phone or smartphone, other mobile device (e.g., e-reader, smartwatch), smart TV (connected directly to the Internet)	First dimension of MCA analysis	van Deursen and van Dijk (2015)	Material Internet Access (single-item scale), Assessed in a binary manner through seven questions about the devices utilized for Internet access: desktop PC, laptop PC, tablet PC, smartphone, game console, TV, e-reader
DS	Skills in using Internet	*Specify your proficiency level in the following skills:* Gathering information, conveying information, resolving software and hardware issues, addressing substantial problems	Eurostat Likert scale, ranging from 1 (no skills) to 4 (highest skills)	Ferrari (2012), Hargittai et al. (2019), van Deursen and Mossberger (2018), van Deursen and van Dijk (2009, 2014), van Dijk and Hacker (2003)	Medium- and Content-related Internet Skills (single-item scale)
IU	Number and variety of different Internet activities participated in online	*Which of the listed activities have you engaged in using the Internet?*	16 binary items representing a diverse set of Internet activities, organized into 4 categories: social interaction, information-seeking, leisure, and commercial transaction	Blank and Groselj (2014); van Deursen and van Dijk (2014, 2015)	Internet Usage (single-item scale), measuring frequency of engagement in twenty-one activities. Items were summed into a single scale that reflected diversity of usage activities

Construct	Definition	Items	Operationalization	References	van Deursen and van Dijk (2015) model
		Social interaction: sending/receiving emails; making phone or video calls over the Internet (e.g., via Skype or Facetime); participating in social networks (such as creating user profiles, posting messages, or contributing to platforms like Facebook); uploading self-generated content (including text, photos, music, videos, software, etc.) to any website for sharing			
		Information-seeking: browsing online news, newspapers, or news magazines; locating information about products or services; searching for health-related information (e.g., injuries, diseases, nutrition, health, etc.); scheduling appointments with a practitioner through a website (e.g., hospital or healthcare centre)			

Construct	Definition	Items	Operationalization	References	van Deursen and van Dijk (2015) model
		Leisure: listening music (e.g., web radio, music streaming); viewing Internet-streamed television (live or catch-up) from broadcasters; streaming video on demand from commercial services (such as Netflix, HBO, etc.); engaging in video gaming			
		Commercial transactions: utilizing travel or accommodation services related to travel; engaging in the sale of goods or services, for instance, through auctions (e.g., eBay); Internet banking; employing payment accounts (e.g., PayPal) to make online purchases of goods or services			

Adapted by Lamberti et al. (2023)

Appendix 2: Outer Model Validation

DS and IU were validated by examining four widely recognized reliability indexes (Hair et al., 2022). These assessments encompassed measures of internal consistency, including Cronbach's α, Dillon's ρ, and Dikstra's ρA, each of which should exceed 0.7. Additionally, the unidimensionality of the constructs was evaluated by comparing the first and second eigenvalues, with preference for the first eigenvalue surpassing 1.

We also scrutinized loading significance based on bootstrap intervals (computed with 500 repetitions) and their length. In the case of reflective indicators, the length of these intervals should be greater than 0.7. Moreover, Average Variance Extracted (AVE) was examined, with a threshold of 0.5 indicating that the constructs account for at least 50% of the variance in the indicators.

The results are presented in Table A1. For DS, both Cronbach's α and Dijkstra's ρ_A surpassed the 0.7 threshold, and for IU, they almost reached it. Dillon's ρ exhibited high values for both constructs. Furthermore, for both DS and IU, only the first eigenvalue of the Principal Component Analysis (PCA) exceeded 1, indicating strong evidence supporting construct unidimensionality. All item loadings either met or exceeded the 0.7 threshold and were statistically significant within the 95% confidence interval. Additionally, AVE values exceeded 0.5 for both DS and IU.

LV	Indicator	Cronbach's α	Dillon-Godstein's ρ	Dijkstra's ρ_A	PCA		AVE	Loadings	95%	
					eigen. 1	eigen. 2			CI	
PA	Physical access (MCA dim. 1)							1		
DS		0.752	0.844	0.758	2.31	0.7	0.575			
	Information							0.725	0.721	0.728
	Communication							0.695	0.692	0.697
	Problem-solving							0.839	0.837	0.841
	Software							0.768	0.765	0.771
IU		0.694	0.813	0.696	2.09	0.797	0.521			
	Social							0.732	0.729	0.734
	Information							0.693	0.689	0.696
	Leisure							0.725	0.723	0.728
	Comm. trans							0.736	0.733	0.738

Author Contributions Conceptualization: GL, JLS; Methodology: GL, GP; Formal analysis and investigation: GL; Writing—original draft preparation: GL, JLS; Writing—review and editing: GL, JLS, and GP; Funding acquisition: JLS.

Funding Open Access Funding provided by Universitat Autonoma de Barcelona. This work was supported by: Grant #2017 SGR 1056 funded by AGAUR-Generalitat de Catalunya, and Grant #870691-INVENT funded by the EU H2020 program.

Data Availability The data underlying this article will be shared on reasonable request to the corresponding author.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Asparouhov, T., Hamaker, E. L., & Muthén, B. (2018). Dynamic structural equation models. *Structural Equation Modeling A Multidisciplinary Journal, 25*(3), 359–388. https://doi.org/10.1080/10705511.2017.1406803

Attewell, P. (2001). Comment: The first and second digital divides. *Sociology of Education, 74*(3), 252–259. https://doi.org/10.2307/2673277

Becker, J. M., Klein, K., & Wetzels, M. (2012). Hierarchical latent variable models in PLS-SEM: Guidelines for using reflective-formative type models. *Long Range Planning, 45*(5–6), 359–394. https://doi.org/10.1016/j.lrp.2012.10.001

Bertrand, F., Sanchez, G., Trinchera, L., & Russolillo, G. (2023). *plspm: Partial Least Squares Path Modeling (PLS-PM)* (0.5.0) [Computer software]. https://cran.r-project.org/web/packages/plspm/index.html

Blank, G., & Groselj, D. (2014). Dimensions of Internet use: Amount, variety, and types. *Information Communication Society, 17*(4), 417–435. https://doi.org/10.1080/1369118X.2014.889189

Crocetta, C., Antonucci, L., Cataldo, R., Galasso, R., Grassia, M. G., Lauro, C. N., & Marino, M. (2021). Higher-order PLS-PM approach for different types of constructs. *Social Indicators Research, 154*(2), 725–754. https://doi.org/10.1007/s11205-020-02563-w

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly, 39*(2), 297–316. https://doi.org/10.25300/MISQ/2015/39.2.02

Drton, M., Fox, C., & Wang, Y. S. (2019). Computation of maximum likelihood estimates in cyclic structural equation models. *The Annals of Statistics*. https://doi.org/10.1214/17-AOS1602

Esposito Vinzi, V., Chin, W. W., Henseler, J., & Wang, H. (Eds.). (2010). *Handbook of Partial Least Squares: Concepts, Methods and Applications*. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-32827-8

Ferrari, A. (2012). Digital competence in practce: An analysis of frameworks. *Publications Office of the European Union*. https://doi.org/10.2791/82116

Greenacre, M., & Blasius, J. (2006). *Multiple Correspondence Analysis and Related Methods. Statistics in the Social and Behavioral Sciences Series.* Chapman & Hall/CRC.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (Third edition). SAGE.

Hargittai, E. (2002). Second-level digital divide: Differences in people's online skills. *First Monday*. https://doi.org/10.5210/fm.v7i4.942

Hargittai, E., & Hinnant, A. (2008). Digital inequality: Differences in young adults' use of the internet. *Communication Research, 35*(5), 602–621. https://doi.org/10.1177/0093650208321782

Hargittai, E., Piper, A. M., & Morris, M. R. (2019). From Internet access to Internet skills: Digital inequality among older adults. *Universal Access in the Information Society, 18*(4), 881–890. https://doi.org/10.1007/s10209-018-0617-5

Hargittai, E., & Shafer, S. (2006). Differences in actual and perceived online skills: The role of gender. *Social Science Quarterly, 87*(2), 432–448. https://doi.org/10.1111/j.1540-6237.2006.00389.x

Hyttinen, A., Eberhardt, F., & Hoyer, P. O. (2012). Learning linear cyclic causal models with latent variables. *Journal of Machine Learning Research, 13*(109), 3387–3439.

Keil, M., Tan, B. C. Y., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *MIS Quarterly, 24*(2), 299. https://doi.org/10.2307/3250940

Kuhlemeier, H., & Hemker, B. (2007). The impact of computer use at home on students' Internet skills. *Computers & Education, 49*(2), 460–480. https://doi.org/10.1016/j.compedu.2005.10.004

Lamberti, G., Lopez-Sintas, J., & Sukphan, J. (2023). Explaining the digital divide in the European Union: The complementary role of information security concerns in the social process of Internet appropriation. *Information Technology for Development*. https://doi.org/10.1080/02681102.2023.2202640

Lamberti, G., Lopez-Sintas, J., & Sukphan, J. (2021). The social process of Internet appropriation: Living in a digitally advanced country benefits less well-educated Europeans. *Telecommunications Policy, 45*(1), 102055. https://doi.org/10.1016/j.telpol.2020.102055

Lê, S., Josse, J., & Husson, F. (2008). FactoMineR: An *R* package for multivariate analysis. *Journal of Statistical Software*. https://doi.org/10.18637/jss.v025.i01

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, yet forsaken? introducing a cross-validated predictive ability test in partial least squares path modeling. *Decision Sciences, 52*(2), 362–392. https://doi.org/10.1111/deci.12445

Mossberger, K., Tolbert, C. J., & Hamilton, A. (2012). Broadband adoptionl measuring digital citizenship: mobile access and broadband. *International Journal of Communication, 6*, 37.

Norris, P. (2001). *Digital Divide: Civic Engagement, Information Poverty, and the Internet Worldwide*. Cambridge University Press.
Parsons, C., & Hick, S. F. (2008). Moving from the Digital Divide to Digital Inclusion. *Currents: Scholarship in the Human Services*, *7*(2). https://journalhosting.ucalgary.ca/index.php/currents/article/view/15892
Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal, 27*(3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003
Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research, 69*(10), 3998–4010. https://doi.org/10.1016/j.jbusres.2016.06.007
Sharma, P. N., Liengaard, B. D., Hair, J. F., Sarstedt, M., & Ringle, C. M. (2023). Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT. *European Journal of Marketing, 57*(6), 1662–1677. https://doi.org/10.1108/EJM-08-2020-0636
Sharma, P. N., Shmueli, G., Sarstedt, M., Danks, N., & Ray, S. (2021). Prediction-oriented model selection in partial least squares path modeling. *Decision Sciences, 52*(3), 567–607. https://doi.org/10.1111/deci.12329
Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics Data Analysis, 48*(1), 159–205. https://doi.org/10.1016/j.csda.2004.03.005
Ullman, J. B., & Bentler, P. M. (2012). Structural Equation Modeling. In I. Weiner (Ed.), *Handbook of Psychology, Second Edition* (1st ed.). Wiley. https://doi.org/10.1002/9781118133880.hop202023
van Deursen, A. J. A. M., & Helsper, E. J. (2015). The Third-Level Digital Divide: Who Benefits Most from Being Online? In L. Robinson, S. R. Cotten, J. Schulz, T. M. Hale, & A. Williams (Eds.), *Studies in Media and Communications* (Vol. 10, pp. 29–52). Emerald Group Publishing Limited. https://doi.org/10.1108/S2050-206020150000010002
van Dijk, J. A. G. M. (2002). *A framework for digital divide research*. https://www.semanticscholar.org/paper/A-framework-for-digital-divide-research-Dijk/cc95f1c3bf0fd65e98b58a469a0af6ee2180ff95
van Dijk, J. A. G. M. (2005). *The Deepening Divide: Inequality in the Information Society* (Edición: 1). SAGE Publications, Inc.
van Dijk, J. A. G. M. (2012). The evolution of the digital divide—The digital divide turns to inequality ofskills and usage. *Digital Enlightenment Year Book, 2012*, 57–75.
van Deursen, A. J. A. M., & Mossberger, K. (2018). Any thing for anyone? a new digital divide in internet-of-things skills. *Policy and Internet, 10*(2), 122–140. https://doi.org/10.1002/poi3.171
van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2009). Using the Internet: Skill related problems in users' online behavior. *Interacting Computers, 21*(5–6), 393–402. https://doi.org/10.1016/j.intcom.2009.06.005
van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2014). The digital divide shifts to differences in usage. *New Media Society, 16*(3), 507–526. https://doi.org/10.1177/1461444813487959
van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2015). Toward a multifaceted model of internet access for understanding digital divides: An empirical investigation. *The Information Society, 31*(5), 379–391. https://doi.org/10.1080/01972243.2015.1069770
van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2019). The first-level digital divide shifts from inequalities in physical access to inequalities in material access. *New Media & Society, 21*(2), 354–375. https://doi.org/10.1177/1461444818797082
van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics, 34*(4–5), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004
van Dijk, J. A. G. M. (2020). *The Digital Divide*. John Wiley & Sons.
van Dijk, J. A. G. M., & Hacker, K. (2003). The digital divide as a complex and dynamic phenomenon. *The Information Society, 19*(4), 315–326. https://doi.org/10.1080/01972240309487
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425. https://doi.org/10.2307/30036540
Wold, H. (1985). Partial Least Squares. In *Encyclopedia of Statistical Sciences* (pp. 581–591). Wiley & Sons.
Wold, H. (1982). Soft modeling: The basic design and some extensions. In K. G. Jöreskog & H. Wold (Eds.), *Systems under indirect observation* (Vol. 2, pp. 1–54). North-Holland.
Zillien, N., & Hargittai, E. (2009). Digital distinction: Status-specific types of internet usage. *Social Science Quarterly, 90*(2), 274–291. https://doi.org/10.1111/j.1540-6237.2009.00617.x

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.