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CHAPTER 24

Joint Longitudinal and Survival Models to Study Vulnerability Processes

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In the field of vulnerability studies, researchers traditionally use static statistical models to explain the occurrence of events of interest, but these models unfortunately do not consider the dynamic nature of life trajectories. Researchers often investigate whether social or psychological resources at a given point in time influence the risk of entering a vulnerable state, whereas it may make more sense to enquire about the preceding evolution of these resources over time. In this chapter, we will first explain how jointly considering the relationship between individuals' longitudinal trajectories on a continuous variable and the risks of occurrence of an event

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of interest can enhance our understanding of vulnerability processes. We will then give a brief overview of joint modelling (JM), a combination of longitudinal mixed-effects models (LMEM) and time-to-event survival models relying on Bayesian estimation. These models simultaneously analyse how continuous and dichotomous outcomes evolve over time and, more importantly, how they relate to each other.[1] Using data collected within the Swiss Household Panel (SHP, 2020), we will provide an illustration of JM, relating the evolution of older participants' self-perception over 9 years to their risk of dropping out of the study due to death or health-related issues. Finally, in the last section of the chapter, we will discuss in more detail how researchers may tailor these statistical models to enquire about the various dimensions of the LIVES approach to vulnerability.

On the Usefulness of JM for Studying Vulnerability Over the Life Course

Vulnerability processes unfold throughout the life course as the interplay among resources, reserves, and stressors (Spini et al., 2013, 2017b). Vulnerability results from a three-step process in which individuals are unable to avoid, efficiently cope with, and recover from various individual, social or environmental stressors (Spini & Widmer, in the present volume). Biological, psychological, social, or environmental resources and reserves evolve and accumulate over the years and may, consequently, lead to a manifest state of vulnerability when they no longer suffice to counter the effects of chronic or nonnormative stressors (Cullati et al., 2018). By studying the dynamics between resources, reserves, and stressors, researchers aim to understand if, when, and what individuals will experience vulnerability in one or multiple life domains.

From a statistical point of view, researchers can model the process of vulnerability as the influence of levels (intercepts) and evolution (slopes) of resources, reserves, and stressors over time on the risk of occurrence of

[1] This chapter targets social scientists with basic quantitative skills and an interest in longitudinal data. We refer the readers to Singer and Willett (2003) for introductory reading on longitudinal LMEM and Kleinbaum and Klein (2012) for time-to-event survival models. For a practical tutorial on JM in R, we refer to Cekic et al. (2021).

a harmful event of interest. The former can be assessed by continuous variables (e.g., number of years of education, income, score on a depression scale), whereas the latter is indicated by a dichotomous yes/no variable (e.g., divorcing, having cancer, receiving social assistance, being promoted at work, losing one's job, entering a nursing home, dying). For instance, one may posit that solo working mothers face a higher risk of burnout when their social support within the community decreases over time (e.g., Robinson et al., 2014) or that an acceleration in cognitive decline may be associated with higher risks of being diagnosed with dementia in late life (McArdle et al., 2005). To properly answer these kinds of questions, many scholars in the field have stressed the importance of longitudinal designs that collect both continuous and dichotomous measures to study individual trajectories of vulnerability throughout various life domains (Baltes & Nesselroade, 1979; Ghisletta & Fürst, 2014; Spini et al., 2017a). Sadly, researchers often fail to maximise the usefulness of such comprehensive longitudinal databases because they lack accessible statistical tools to treat this rich and complex data.

In social sciences and psychology, researchers usually analyse the longitudinal trajectories of continuous variables (such as resources and reserves) and the probability of an event's occurrence over time (vulnerability outcome) separately. Scholars often use longitudinal LMEM for the former (e.g., Singer & Willett, 2003) and survival analysis models, such as Cox proportional hazards regression (e.g., Kleinbaum & Klein, 2012), for the latter. One inefficient, and at times biased, approach combines the two types of analysis by first estimating longitudinal LMEM and then entering the corresponding individual estimates about the trajectories as covariates in a subsequent survival model (Rizopoulos, 2012). However, these two-step approaches neither consider that trajectories of continuous variables across time may influence the occurrence of an event of interest nor that the latter may condition the former (cf., reverse causality, see Lewis, 1974). For example, one's risk of receiving a diagnosis of dementia not only depends on one's cognitive decline but also likely shapes one's cognitive trajectory years before the malignant event. JM precisely bridges that reciprocity gap by jointly (i.e., simultaneously) estimating the risk of occurrence of an event of interest contingent upon the longitudinal process, and the other way around. Applied to the study of vulnerability, JM allows researchers to test whether and how the level (i.e., intercept) and/or evolution (i.e., slope) of resources across time are (bidirectionally) linked to the risk of encountering a stressor or entering a vulnerable state.

To date, only a few studies have applied JM to assess the role of longitudinal trajectories of various psychological, cognitive or health-related resources to predict longevity and the risk of receiving a dementia diagnosis or dying. For instance, Zhang et al. (2009) showed that the mortality risk in older adults whose depressive symptoms grew annually by one point increased by 57% compared to those with stable depressive symptoms. In cancer patients, Kypriotakis et al. (2016) reported a predictive effect of both the level of and change in quality of life on survival rates. Patients with higher baseline levels of quality of life had higher chances of survival, and more importantly, each one-unit increase in the trajectory of quality of life across time decreased the risk of death by 82%. Regarding cognitive abilities, levels of and/or rate of change in memory, processing speed, or verbal fluency also predicted both risk of dying and/or being diagnosed with Alzheimer's disease (Ghisletta, 2008; Ghisletta et al., 2006; McArdle et al., 2005; Muniz-Terrera et al., 2011). Moreover, Aichele et al. (2021) compared direct predictions from a JM to those of a two-step estimation procedure and showed that JM has greater power to estimate associations between cognitive decline and mortality in a large sample of adults. Based on these encouraging results in the health and cognitive literature, we therefore advocate that researchers consider JM a promising statistical tool to further the understanding of vulnerability processes throughout the life course.

Introduction to JM

Some scholars have studied the association between the occurrence of an event and life-course trajectories on continuous variables by applying two separate LMEMs to participants who have experienced the event and to those who have not. The difference in parameter estimates between the two sets of models is then imputed to the occurrence of the event. Although this approach serves the purpose of separately describing trajectories for the event-positive and event-negative participants, it assumes that the two groups stem from different populations and cannot allow for the direct reciprocal influence between the event and the trajectories. In other words, analysing separate trajectories for event-positive and event-negative participants relies on the assumption that participants fundamentally differ across their entire life course and that the event is bound to occur (or not) according to group membership. However, not having experienced the event at a given time point does not preclude the event from happening later on (e.g., not having divorced or received a medical diagnosis in the past does not protect individuals from these events occurring in the future). JM, instead, considers all participants as stemming from the same population, as is customary in survival analyses, and explicitly estimates individual risks of the event occurring, given that it has not yet occurred. JM thus accounts for both complete and censored data (i.e., data for both event-positive and event-negative participants). As such, joint models avoid estimation biases caused by nonrandom dropout (Little & Rubin, 1987). In addition, JM differs markedly from the combination of sequence analysis and survival analysis with respect to the nature of the longitudinal phenomenon. JM estimates trajectories of continuous longitudinal data, while the combination of sequence and survival analyses models longitudinal data as a sequence of various events over time and how transitioning from one state to another may influence the occurrence of the event of interest (e.g., does transitioning from married to widowed influence the risk of receiving social assistance? cf. the chapter by Studer, Gauthier, & Le Goff in this volume).

In JM, two submodels are simultaneously estimated, one for the longitudinal continuous portion and one for the time-to-event portion of the data. We refer the reader to Appendix A of the Supplementary Material for the decomposition of the joint model into equations corresponding to the LMEM and the time-to-event submodels and the association between the two through the shared parameters. The former (LMEM) submodel models the trajectory of the dependent longitudinal variable. It allows for the estimation of both fixed and random effects as a function of the intercept, time (i.e., the slope), and, if included, additional independent variables (Eq. (A.1) in Appendix A). While fixed effects correspond to mean effects (i.e., at the group level), random effects correspond to deviations from this mean group-level effect for each given individual in the sample. In other words, random effects indicate the extent to which a given participant deviates from the average intercept (i.e., general level) or slope (i.e., change across time). To put it simply, the LMEM submodel estimates parameters describing how the longitudinal variable of interest changes over time at the group level and how individuals differ both in their initial level (i.e., intercept) and change (i.e., slope) on this variable. In the time-to-event submodel (Cox proportional hazard), the risk of event occurrence depends on both a baseline hazard function that varies with time (i.e., the risk of event occurrence at a given time point, given that it has not occurred yet) and, possibly, individual differences in independent variables of interest (Eq. (A.2) in Appendix A). In other words, this submodel describes how the risk of event occurrence evolves over time and how participant characteristics affect this risk.

The two submodels are then joined through a conditional joint density estimation, whereby the time-to-event and longitudinal processes are conditional upon each other (e.g., Hogan & Laird, 1997; Papageorgiou et al., 2019; Wulfsohn & Tsiatis, 1997; see Eq. (A.3) in Appendix A). Thus, in the joint model, the probability of event occurrence at any given time point depends on (a) elapsed time, (b) individual differences in independent variables, and (c) the current value and/or trajectory of the longitudinal variable over time. In simpler terms, this means that the joint model allows for reciprocal effects between the longitudinal and survival components. The longitudinal trajectory is thus not only defined as a function of an individual intercept, slope, and possible other independent variables but also depends on an individual's risk of an upcoming event occurrence. Likewise, an individual hazard of the event occurring depends not only on that individual's baseline hazard function and possible other independent variables but also on his or her previous trajectory on the longitudinal dependent variable. The exact form of the relationship between the longitudinal process from the LMEM and the probability of occurrence of the event (point (c)) depends on the selected association function for the joint model.

Various types of association between the longitudinal and time-to-event portions of the model are available, thereby allowing the quantification of both the nature and strength of this association. For space reasons, we present the shared-random effect linking function only (see Rizopoulos et al., 2014), which specifies that random effects (typically from intercept and slope) in the longitudinal submodel (Eq. (A.1) in Appendix A) be inserted as predictors of the time-to-event submodel (Eq. (A.2) in Appendix A). Accordingly, the association parameter vector (in Eq. (A.3) in Appendix A) indicates the change in the log hazard for a one-unit change in individuals' deviations from the average linear mixed intercept or slope. In other words, the joint model assesses to what extent deviating from the average general level and/or change in the longitudinal variable influences the risk of occurrence of the event and quantifies the *strength* of this association. Practically, these models allow for testing whether individuals who have a higher/lower general level (random intercept) or a steeper decline/increase (random slope) in the continuous variable have a higher/lower risk of experiencing the dichotomous event of interest. For instance, one could test whether participants who show lower general health status and/or a steeper decline in their health status are at higher risk of dying before the end of the study than those who display an average health level and/or rate of decline.

For further detail and other parametrisation functions, we refer the reader to Cekic et al. (2021), who provided a comprehensive and accessible tutorial for JM using the JMbayes package (Rizopoulos, 2016) in R (R Development Core Team, 2020). We also briefly mention other parametrisation functions in the last section of this chapter.

Illustration of JM with Data from the Swiss Household Panel

Database and Hypotheses

For didactic purposes in this chapter, we analysed a subset of data from the Swiss household panel (SHP, 2020). To do so, we used R and relied in particular on the JMbayes package (Rizopoulos, 2016; all R syntax is presented and commented on in Appendix B). The SHP is a nationally representative annual panel study to observe dynamics of living and social condition changes in Switzerland since 1999. The study included questionnaires related to various aspects of participants' characteristics and living conditions, such as sociodemographics, employment, life events, health, education, income, social networks, leisure and psychological resources. For illustration purposes, we focused our analysis on psychological resources and did not investigate the additional role of biological (except for biological sex) or social resources. As previous studies have shown that self-reported evaluations of one's functioning strongly predict mortality risk (e.g., Kaplan et al., 1988), we investigated the predictive role of self-reported psychological resources on health frailty in older adults.

We focused our analysis on a very general measure of personal perception of the self (self-perception), included in the SHP. Self-perception indicates the extent to which participants feel that they exert an impact on their own destiny and are able to make decisions for themselves (as opposed to their destiny and decisions being dictated by external factors over which they have no control; see Voorpostel et al., 2018). Self-perception was measured via six items from self-mastery, self-efficacy, and self-esteem scales (Levy et al., 1997; Rosenberg, 1965). We aimed to investigate how self-perception evolves with advancing age and whether and how it may inform risks of dropping out of the study due to death or health-related vulnerability in old age (see Rothenbühler & Voorpostel, 2016 for analysis of nonrandom dropout in SHP data). Addressing this question with a JM is highly appropriate because participants' trajectories of self-perception may inform their risk of dying or having serious health-related issues inasmuch as imminent death or altered health state may impact their level of perceived self-perception.

Because the risk of dying in younger participants is low, we included participants aged 65 or older in 2009 who personally responded to a minimum of two of four waves, resulting in a sample of 1632 individuals. Self-perception was measured every 3 years since wave 11 of SHP—in 2009, 2012, 2015 and 2018—via a 6-item scale with items such as 'I have little influence on life events'. Responses were rated from 0 ('I completely disagree') to 10 ('I completely agree'). We followed SHP guidelines to compute the mean of the six items after recoding items with reversed valence (Voorpostel et al., 2018). For the event, we used the variable *RNPX* of the SHP dataset and computed our dichotomous event of interest, namely, being unable to participate in the study anymore because one died (coded as '2' in the original database), was institutionalised (coded as '3'), or had problems due to age or health (coded as '8'). The event of interest occurred for 209 (12.8%) participants before the last wave. Figure 24.1 depicts participants' longitudinal trajectories for self-perception separately for participants who were and were not able to pursue participation in the study by 2018. Participants were measured at least twice out of the four occasion measurements.

Initially, we hypothesised that (1) participants' decrease in self-perception with increasing age and both (2) a lower baseline level and (3) a steeper decline in self-perception would increase the risk of being unable to continue participating in the study due to health-related issues or death (e.g., Lee et al., 2016; Orth et al., 2010). We controlled for participants' age at their first wave of measurement (*AgeEntry*) and biological sex (*Sex*), given that life expectancy is longer for females than for males (Federal Statistical Office Section Demography and Migration, 2019).

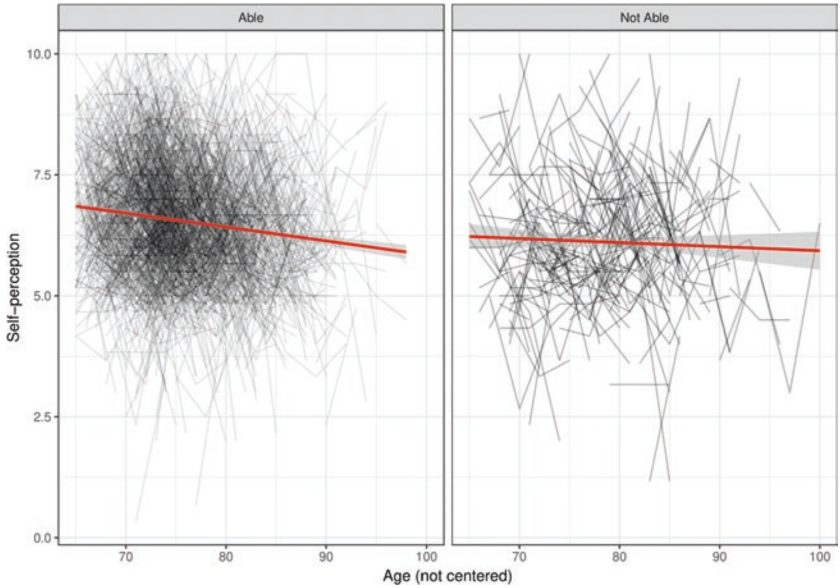

Fig. 24.1 Lineplot of individual trajectories for self-perception by participation status by the last wave. (Data source: Swiss Household Panel (SHP))

Analyses and Results

Following Cekic et al. (2021), data were analysed in three successive steps in R using the packages nlme, survival, and JMbayes. First, we estimated the longitudinal submodel, then the time-to-event submodel, and finally the joint model. As the specification of the joint model depends on the results from the two submodels, we report below the analytical strategy and corresponding results for each of the three steps sequentially.

Longitudinal Submodel

In the first step, we estimated four LMEMs to select the best fit for the mixed-effects subpart of the joint model (we refer the reader to Eq. (A.4) in Appendix A for equations of predictions for the LMEM models). First, we modelled change in self-perception as a function of a random intercept, the fixed effect of Age (centred at age 65 years, *Age_65*, the time-varying variable in this model), and controlling for initial Age (*AgeEntry*) (*M0*). In other words, *M0* proposes that individuals differ with respect to their initial level of self-perception and that self-perception varies according to participants' current age and age at first measurement. However, given that there are no random effects associated with *Age_65*, the model assumes that all participants change at the same rate. Then, in model M1, we added the random effects of *Age_65* (and its covariance with the random intercept) to the previous model *M0*, acknowledging the possibility that participants' self-perception may change at various rates as they age. In the last two models, we tested the additional contribution of quadratic (Age_65^2) and cubic (Age_65^3) fixed effects of age (*M2* and *M3*, respectively). Compared to *M0* and *M1*, the last two models imply an accelerated decline in self-perception with increasing age (in a quadratic form for *M2* and a cubic form for *M3*). The four models can be written as follow:

$$
\begin{aligned}
M0: y_i(t) &= (\beta_0 + b_{0i}) + \beta_1 Age\_65_i(t) + \beta_4 AgeEntry_i + e_i(t),\\
M1: y_i(t) &= (\beta_0 + b_{0i}) + (\beta_1 + b_{1i}) Age\_65_i(t) + \beta_4 AgeEntry_i + e_i(t),\\
M2: y_i(t) &= (\beta_0 + b_{0i}) + (\beta_1 + b_{1i}) Age\_65_i(t)\\
&\quad + \beta_2 Age\_65_i(t)^2 + \beta_4 AgeEntry_i + e_i(t),\\
M3: y_i(t) &= (\beta_0 + b_{0i}) + (\beta_1 + b_{1i}) Age\_65_i(t) + \beta_2 Age\_65_i(t)^2\\
&\quad + \beta_3 Age\_65_i(t)^3 + \beta_4 AgeEntry_i + e_i(t),
\end{aligned}
$$

where $y_i(t)$ denotes self-perception for individual i at time t, betas denote fixed effects, and b_{0i} and b_{1i} denote random effects for the intercept and slope, respectively.

We selected the best model based on Bayesian information criterion (BIC) values, with smaller BIC values indicating better fit. We used a threshold of a 6-point difference in BIC values as strong evidence against the model with the highest BIC (Kass & Raftery, 1995). Based on BIC values, we retained M0 as the best model given the data (as indicated by a BIC value of 15,225.55 for 5 degrees of freedom versus 15,232.22, 15,239.68 and 15,248.08 with 7, 8, and 9 degrees of freedom, respectively, for models M1, M2 and M3). The model explained 48% of the variance in the data, as indicated by the conditional R-square.

As presented in Table 24.1 and in line with our first hypothesis, the data showed a linear decline in self-perception with increasing age. There was also a positive effect of *AgeEntry* such that the older the participants were at the first measured wave, the higher their self-perception. This result

Table 24.1 Parameter estimates for longitudinal submodel M0

Random Effects	*Variance*	*SD*			
Intercept	0.796	0.892			
Residual	0.889	0.943			
Fixed Effects	*Estimate*	*SE*	*df*	*t*	*p*
Intercept	5.442	0.422	3189	12.889	<0.001
Age _ 65	-0.046	0.005	3189	-9.506	<0.001
AgeEntry	0.021	0.006	1630	3.420	<0.001

Note: Data source: Swiss Household Panel (SHP)

most likely reflects a selection effect, such that the oldest individual might not decide to participate in the study unless he or she had a high sense of personal competence. The random effects of the intercept substantively contributed to the model, given that 47% of the variance in self-perception over time was due to differences between subjects, as indicated by the intraclass coefficient.

Of importance, adding the random effect of the slope did not substantially improve model fit, and the addition of this effect to the model only increased the explained percent of variance by 0.9%. Critically, due to a computational issue, *M1* did not provide realistic estimates for the random slope of *Age_65* (ultimately resulting in uninterpretable results in the joint model—not presented in the present chapter). It is well known that the power for variance in slope can be quite limited in these kinds of models (Hertzog et al., 2008). Hence, the longitudinal submodel did not adequately capture interindividual differences in steepness of decline for self-perception across time. Thus, although there appeared to be differences between individuals in the steepness of their self-perception decline with increasing age (see Fig. 24.1), the model did not adequately capture interindividual differences in change. Similarly, the fixed quadratic and cubic linear effects of age neither reached significance nor proved useful in explaining the data, as indicated by the increase in BIC from *M1*, *M2*, and *M3*, respectively.

Time-to-Event Submodel

Then, for the time-to-event data, we estimated the Cox proportional hazards model with *Sex* and *AgeEntry* as covariates. One assumption of these time-to-event models is that the baseline hazard function (i.e., the risk of the event occurring given that it has not yet occurred; see Eq. (A.2) in Appendix A) is proportional for each predictor. This assumption was met for *Sex*, as indicated by the nonsignificant Schoenfeld residuals test ($\chi^2 = 1.13$, $df = 1$; $p = 0.29$). However, baseline hazard functions were not proportional for *AgeEntry* ($\chi^2 = 8.40$, $df = 1$; $p < 0.01$), meaning that the risk of event occurrence over time differed based on age at first wave of measurement. We thus stratified the time-to-event analysis by *AgeEntry* by using two arbitrary strata for participants 65–75 years old and those 76 or older. In other words, the final Cox proportional hazard model accounted for differences in baseline hazard function between individuals who were 75 or younger versus 76 or older at the first wave of measurement (for further explanation, see Cekic et al., 2021; Cox, 1972; Fox & Weisberg, 2011).

In stratification procedures, the corresponding variable is considered for the estimation of the Cox model but does not appear as a predictor in the model outputs (as denoted by the subscript k in Eq. (A.5) in Appendix A). Model estimates using the stratification procedure are presented in Table 24.2.

The results from the time-to-event submodel therefore indicated that sex did not affect the risk of dropping out of the study due to dying, health reasons or institutionalisation. This result is also apparent in the corresponding Kaplan–Meier curve for survival by sex (see Fig. 24.2), which depicts a clear overlap of the survival probabilities (i.e., still being able to participate in the study) for women and men, at least until age 85. Although the effect of *Sex* was nonsignificant, we kept this variable in the model for the following joint modelling step for didactic purposes.

Joint Model

Finally, based on the selected submodels (*M0* and Cox proportional hazard model with stratification for *AgeEntry*), we estimated the joint model with the shared random effects parametrisation (see Eq. (A.6) in Appendix A). Given that the longitudinal submodel we retained included a random

Table 24.2 Parameter estimates for the Cox proportional hazard submodel

	coef	*exp(coef)*	*SE(coef)*	*z*	*p*
Sex	-0.112	0.894	0.141	-0.793	0.428

Note: Data source: Swiss Household Panel (SHP)

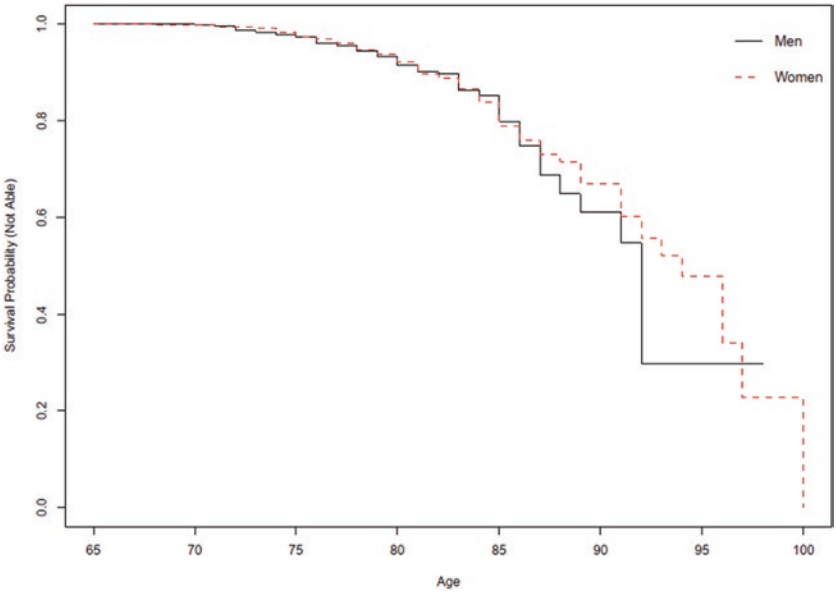

Fig. 24.2 Kaplan–Meier estimator of survival probabilities for men and women (Data source: Swiss Household Panel (SHP))

effect only for the intercept (i.e., the model only accounted for interindividual variations on the baseline level of self-perception), we only had one association parameter in our model, which quantified the strength of the association between deviations from the initial group level of self-perception and risks of being unable to participate in the study due to death, health reasons or institutionalisation (corresponding to our second hypothesis). Indeed, the absence of a random slope in *M0* subsequently prevented us from testing the association between the steepness of decline in self-perception and our event of interest (our third hypothesis). The results for the joint model are reported in Table 24.3. We made inferential decisions regarding the results based on the credible intervals at 95% for the estimated parameters, following Bayesian estimation.

The results for the longitudinal process within the joint model were almost identical to those obtained for the longitudinal submodel (reported in Table 24.1). However, the results differed for the time-to-event portion of the model. Indeed, while the effect of *Sex* was not significant in the Cox

Table 24.3 Parameter estimates and 95% credible intervals for the joint model using shared-random effects association

	Value	*SE*	*2.5%*	*97.5%*
Sex	-0.295	0.011	-0.5744	-0.011
Assoct : (*intercept*)	-0.5126	0.003	-0.711	-0.307
tauBs	89.219	14.971	11.380	386.509
Intercept	5.240	0.007	4.614	5.847
Age _ 65	-0.047	0.001	-0.051	-0.044
AgeEntry	0.024	0.001	0.016	0.033
D[1, 1]	0.796			

Note: Upper and lower panels correspond to estimates for the time-to-event and longitudinal processes, respectively. *tauBs* is a parameter related to the baseline hazard function and is typically not interpreted. *D*[1, 1] denotes the variance of the random intercept from the longitudinal subprocess. Data source: Swiss Household Panel (SHP)

proportional hazards submodel (reported in Table 24.2), it emerged in the joint model (given that 0 is not included in the 95% credible interval). Hence, when the longitudinal process and the association between the general baseline level of self-perception were controlled, the effect of *Sex* reached significance. This effect was probably driven by the difference in survival probability from age 85 onwards (see Fig. 24.2). However, most importantly regarding our hypothesis, the association parameter α (denoted as *Assoct* : (*intercept*) in Table 24.3 and in the R output) was negative and significant, meaning that individuals who had lower general levels of self-perception than the average of the sample at baseline were more likely to drop out of the study due to health reasons or dying. The hazard ratio for a one-unit increase from individual deviation from the general mean of the intercept is $exp(\alpha) = exp(-0.513) = 0.599$. We can calculate the risk reduction as $1 - exp(\alpha) = 1 - exp(-0.513) = 0.401$. In other words, participants who were more confident by one unit in their own ability to cope with life events at their first measurements were 40.1% less likely to quit the study because of death, institutionalisation or health-related issues compared to participants with average levels of self-perception at age 65.

To summarise, our analyses revealed (a) that participants who were older at the first wave of measurement had a higher level of self-perception than their younger counterparts, probably reflecting a selection effect (i.e., older individuals who had low levels of self-perception might not have enrolled in the study). Furthermore, and in line with Orth et al. (2010), controlling for sex and age at first measurement, joint modelling allowed us to show that (b) self-perception generally declined with advancing age. Finally, similar to Lee et al. (2016), who reported that high levels of personal mastery dampened the effects of frailty on physical function, (c) individuals who had higher levels of self-perception at age 65 were 40.1% less likely to drop out of the study due to death, institutionalisation or health issues. However, we did not find conclusive evidence for interindividual differences in steepness of decline, which prevented us from studying whether individual trajectories of self-perception across time were associated with risks of being unable to pursue study participation. Overall, these results stress that older adults' perception of their ability to influence the course of their lives and the evolution of their physical and autonomy status intertwine. They further show that psychological resources—simply evaluated through six quick questions—can prove useful to predict frailty or death years later (also see Hülür et al., 2017).

Future Directions in Using Joint Modelling for Studying Vulnerability as a Process

In this chapter, we presented an example of JM using the *shared random effects* parametrisation, which is the most accessible and intuitive JM parametrisation that answers the question 'Does an individual with higher/lower value than average have an increased risk of event occurrence?' However, more complex parametrisations (see Cekic et al., 2021; Rizopoulos, 2012, 2016) provide analytical flexibility for testing a wide array of theoretical hypotheses, such as 'Does the current value on the time-varying variable influence the risk of event occurrence, irrespective of this variable's trajectory?' (*current value association*) or 'Does the rate of change in the longitudinal variable predict the risk of event occurrence?' (*current value plus slope association*). More broadly, given the possibility of adding both continuous or dichotomous and time-invariant or time-varying covariates to the model, JM can accommodate a wide array of variables of interest for studying vulnerability in the life course. As detailed below, this analytical technique thus appears to be a promising tool for investigating the multidimensional, multilevel, and multidirectional aspects of vulnerability.

In relation to the LIVES approach to vulnerability from a life-course perspective, JM can prove useful in studying the multidimensional aspects of the vulnerability process (Spini et al., 2017a). Indeed, JM can be applied to analyse how trajectories in one life domain can relate to the occurrence of a given event in another life domain over time (spillover effects, Bernardi et al., 2017; Spini et al., 2017a). These models allow researchers to investigate whether levels of and changes in resources in one life domain (e.g., social policies and/or evolution of social support in individuals' personal lives) may affect the risk of experiencing vulnerability in another domain (e.g., burnout in solo working mothers).

Vulnerability processes not only unfold in different life domains but also occur at multiple levels of analysis at the articulation between individuals and contexts. Given its ability to include both continuous and dichotomous predictors, JM also allows the investigation of multilevel aspects of vulnerability processes. Practically, researchers can model whether factors from the micro and macro levels, as well as their articulation at the meso level, are associated with the occurrence of an event of interest over time. For instance, in a JM model, one can study systemic inequalities in access to higher education across countries by analysing how a country's welfare regime, ethnic/social group belonging and the trajectory of various individuals' resources may predict the chance of being accepted to prestigious school programmes across various countries.

Finally, some advanced applications of JM—cumulative models (see Rizopoulos 2016, pp. 17–18; and Rizopoulos, 2012, pp. 106–111)—may be particularly suited for the study of multidirectionality—the temporal dimension—in the vulnerability process. Within a cumulative disadvantage paradigm, micro (dis)advantages cumulate over the years and lead to drastically different outcomes (Dannefer, 2003). Hence, JM can be tailored to investigate resources or frailty accumulation across the life span or, more generally, variations in life trajectories. JM can specifically model the *cumulative effects* of the longitudinal variable in individuals' life trajectories up to a given point in time through integrals (i.e., the area under the curve for the longitudinal variable), which provides a far better representation of the accumulation of advantages or disadvantages throughout the life span than any regression slope. This is especially true when the trajectory for the longitudinal variable is not monotonic and instead alternatively increases or decreases throughout the life course. An applied example would be investigating how the accumulation (and not merely the slope) of subjective loneliness over the years could accumulate and lead to an increased risk of depression in older adults. These models are hence particularly appropriate for testing how cumulative advantages or disadvantages accumulate over time and whether and how they relate to the likelihood of entering a vulnerable state later on.

To conclude, we deeply believe that JM is a privileged tool to further our understanding of the multidimensional, multilevel and multidirectional perspectives of vulnerability dynamics across the life span. Moreover, JM can also prove useful to gain insight into each of the three steps of the vulnerability process. Indeed, researchers can tailor JM not only to identify which variables and how they evolve over time will predict the likelihood of entering a vulnerable state but also to determine whether individuals will be able to avoid, efficiently cope with, or recover from stressors. Given the extant availability of software to estimate JM (see Cekic et al., 2021), we strongly encourage researchers to consider these models in their methodological approaches to studying vulnerability processes and subsequently to fully exploit the richness of multidisciplinary longitudinal databases.

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References

Aichele, S., Cekic, S., Rabbitt, P., & Ghisletta, P. (2021). Cognition-mortality associations are more pronounced when estimated jointly in longitudinal and time-to-event models. *Frontiers in Psychology, 12*. https://doi.org/10.3389/fpsyg.2021.708361

Baltes, P. B., & Nesselroade, J. R. (1979). History and rationale of longitudinal research. In J. R. Nesselroade & P. B. Baltes (Eds.), *Longitudinal research in the study of behavior and development* (pp. 1–39). Publisher: Academic Press.

Bernardi, L., Bollmann, G., Potarca, G., & Rossier, J. (2017). Multidimensionality of well-being and spillover effects across life domains: How do parenthood and personality affect changes in domain-specific satisfaction? *Research in Human Development, 14*(1), 26–51. https://doi.org/10.1080/15427609.2016.1268893

Cekic, S., Aichele, S., Brandmaier, A. M., Köhncke, Y., & Ghisletta, P. (2021). A tutorial for joint modeling of longitudinal and time-to-event data in R. *Quantitative and Computational Methods in Behavioral Sciences, 1–40*. https://doi.org/10.5964/qcmb.2979

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological), 34*(2), 187–220. JSTOR.

Cullati, S., Kliegel, M., & Widmer, E. (2018). Development of reserves over the life course and onset of vulnerability in later life. *Nature Human Behaviour, 2*(8), 551–558. https://doi.org/10.1038/s41562-018-0395-3

Dannefer, D. (2003). Cumulative advantage/disadvantage and the life course: Cross-fertilizing age and social science theory. *The Journals of Gerontology: Series B, 58*(6), S327–S337. https://doi.org/10.1093/geronb/58.6.S327

Federal Statistical Office Section Demography and Migration. (2019). *Life expectancy*. https://www.bfs.admin.ch/bfs/en/home/statistiken/bevoelkerung/geburten-todesfaelle/lebenserwartung.html

Fox, J., & Weisberg, S. (2011). *Cox proportional-hazards regression for survival data in R: An Appendix to an R companion to applied regression, second edition*. https://socialsciences.mcmaster.ca/jfox/Books/Companion-2E/appendix/Appendix-Cox-Regression.pdf

Ghisletta, P. (2008). Application of a joint multivariate longitudinal–survival analysis to examine the terminal decline hypothesis in the swiss interdisciplinary longitudinal study on the oldest old. *The Journals of Gerontology: Series B, 63*(3), P185–P192. https://doi.org/10.1093/geronb/63.3.P185

Ghisletta, P., & Fürst, G. (2014). Modèles pour données longitudinales. In J. Juhel & G. Rouxel (Eds.), *Approches contemporaines des différences individuelles en psychologie*. Presses universitaires de Rennes.

Ghisletta, P., McArdle, J. J., & Lindenberger, U. (2006). Longitudinal cognition-survival relations in old and very old age. *European Psychologist*. https://econtent.hogrefe.com/doi/abs/10.1027/1016-9040.11.3.204

Hertzog, C., von Oertzen, T., Ghisletta, P., & Lindenberger, U. (2008). Evaluating the power of latent growth curve models to detect individual differences in change. *Structural Equation Modeling: A Multidisciplinary Journal, 15*(4), 541–563. https://doi.org/10.1080/10705510802338983

Hogan, J. W., & Laird, N. M. (1997). Mixture models for the joint distribution of repeated measures and event times. *Statistics in Medicine, 16*(3), 239–257. https://doi.org/10.1002/(SICI)1097-0258(19970215)16:3<239::AID-SIM483>3.0.CO;2-X

Hülür, G., Heckhausen, J., Hoppmann, C. A., Infurna, F. J., Wagner, G. G., Ram, N., & Gerstorf, D. (2017). Levels of and changes in life satisfaction predict mortality hazards: Disentangling the role of physical health, perceived control, and social orientation. *Psychology and Aging, 32*(6), 507–520. https://doi.org/10.1037/pag0000187

Kaplan, G., Barell, V., & Lusky, A. (1988). Subjective state of health and survival in elderly adults. *Journal of Gerontology, 43*(4), S114–S120. https://doi.org/10.1093/geronj/43.4.S114

Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association, 90*(430), 773–795. JSTOR. https://doi.org/10.2307/2291091

Kleinbaum, D. G., & Klein, M. (2012). *Survival analysis: A self-learning text, thirdedition*(3rded.).Springer.https://doi.org/10.1007/978-1-4419-6646-9

Kypriotakis, G., Vidrine, D. J., Francis, L. E., & Rose, J. H. (2016). The longitudinal relationship between quality of life and survival in advanced stage cancer. *Psycho-Oncology, 25*(2), 225–231. https://doi.org/10.1002/pon.3846

Lee, W.-J., Chen, L.-K., Peng, L.-N., Chiou, S.-T., & Chou, P. (2016). Personal mastery attenuates the adverse effect of frailty on declines in physical function of older people. *Medicine, 95*(34), e4661. https://doi.org/10.1097/MD.0000000000004661

Levy, R., Joye, D., Guye, O., & Kaufmann, V. (1997). Représentations. In R. Levy, D. Joye, & O. Guye (Eds.), *Tous égaux? De la stratification aux représentations* (pp. 495–538). Seismo.

Lewis, D. (1974). Causation. *The Journal of Philosophy, 70*(17), 556–567. https://doi.org/10.2307/2025310

Little, R. J. A., & Rubin, D. B. (1987). *Statistical analysis with missing data*. Wiley.

McArdle, J. J., Small, B. J., Bäckman, L., & Fratiglioni, L. (2005). Longitudinal models of growth and survival applied to the early detection of Alzheimer's disease. *Journal of Geriatric Psychiatry and Neurology, 18*(4), 234–241. https://doi.org/10.1177/0891988705281879

Muniz-Terrera, G., Piccinin, A. M., Johansson, B., Matthews, F., & Hofer, S. M. (2011). Joint modeling of longitudinal change and survival. *GeroPsych, 24*(4), 177–185. https://doi.org/10.1024/1662-9647/a000047

Orth, U., Trzesniewski, K. H., & Robins, R. W. (2010). Self-esteem development from young adulthood to old age: A cohort-sequential longitudinal study. *Journal of Personality and Social Psychology, 98*(4), 645–658. https://doi.org/10.1037/a0018769

Papageorgiou, G., Mauff, K., Tomer, A., & Rizopoulos, D. (2019). An overview of joint modeling of time-to-event and longitudinal outcomes. *Annual Review of Statistics and Its Application, 6*(1), 223–240. https://doi.org/10.1146/annurev-statistics-030718-105048

R Development Core Team. (2020). *R: A Language and environment for statistical computing*. http://www.r-project.org/

Rizopoulos, D. (2012). *Joint models for longitudinal and time-to-event data: With applications in R*. Routledge & CRC Press. https://www.routledge.com/Joint-Models-for-Longitudinal-and-Time-to-Event-Data-With-Applications/Rizopoulos/p/book/9781439872864

Rizopoulos, D. (2016). The R package JMbayes for fitting joint models for longitudinal and time-to-event data using MCMC. *Journal of Statistical Software, 72*(1), 1–46. https://doi.org/10.18637/jss.v072.i07

Rizopoulos, D., Hatfield, L. A., Carlin, B. P., & Takkenberg, J. J. M. (2014). Combining dynamic predictions from joint models for longitudinal and time-to-event data using Bayesian model averaging. *Journal of the American Statistical Association, 109*(508), 1385–1397. https://doi.org/10.1080/01621459.2014.931236

Robinson, L. D., Magee, C. A., & Caputi, P. (2014). Social support, work hours and health: A comparative study of sole and partnered Australian mothers. *Women's Studies International Forum, 42*, 19–27. https://doi.org/10.1016/j.wsif.2013.10.010

Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton University Press.

Rothenbühler, M., & Voorpostel, M. (2016). Attrition in the Swiss household panel: Are vulnerable groups more affected than others? In M. Oris, C. Roberts, D. Joye, & M. Ernst Stähli (Eds.), *Surveying human vulnerabilities across the life course* (pp. 223–244). Springer International Publishing. https://doi.org/10.1007/978-3-319-24157-9_10

SHP Group Living in Switzerland Waves 1-20 [Dataset]. FORS – Centre de compétences suisse en sciences sociales. Financed by the Swiss National Science Foundation, distributed by FORS, Lausanne. (2020). https://doi.org/10.23662/FORS-DS-932-3

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford University Press.

Spini, D., Bernardi, L., & Oris, M. (2017a). Toward a life course framework for studying vulnerability. *Research in Human Development, 14*(1), 5–25. https://doi.org/10.1080/15427609.2016.1268892

Spini, D., Bernardi, L., & Oris, M. (2017b). Vulnerability across the life course. *Research in Human Development, 14*(1), 1–4. https://doi.org/10.1080/15427609.2016.1268891

Spini, D., Hanappi, D., Bernardi, L., Oris, M., & Bickel, J.-F. (2013). Vulnerability across the life course: A theoretical framework and research directions. *LIVES Working Papers, 2013*(27), 1–35. https://doi.org/10.12682/lives.2296-1658.2013.27

Spini, D., & Widmer, E. (this volume). Inhabiting vulnerability throughout the life course. In D. Spini & E. Widmer (Eds.), *Withstanding vulnerability throughout adult life. Dynamics of stressors, resources, and reserves*. Palgrave Macmillan.

Voorpostel, M., Tillmann, R., Lebert, F., Kuhn, U., Lipps, O., Ryser, V.-A., Antal, E., Monsch, G.-A., Dasoki, N., & Wernli, B. (2018). *Swiss household panel userguide (1999–2017), Wave 19, December 2018*. FORS.

Wulfsohn, M. S., & Tsiatis, A. A. (1997). A joint model for survival and longitudinal data measured with error. *Biometrics*, *53*(1), 330–339. JSTOR. https://doi.org/10.2307/2533118

Zhang, J.-P., Kahana, B., Kahana, E., Hu, B., & Pozuelo, L. (2009). Joint modeling of longitudinal changes in depressive symptoms and mortality in a sample of community-dwelling elderly people. *Psychosomatic Medicine, 71*(7), 704–714. https://doi.org/10.1097/PSY.0b013e3181ac9bce