SSM - Population Health 13 (2021) 100744

Contents lists available at ScienceDirect

SSM - Population Health

journal homepage: http://www.elsevier.com/locate/ssmph

Does social support mediate the effect of multimorbidity on mental wellbeing in the German working population? A longitudinal mediation analysis using structural equation modelling

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A R T I C L E I N F O

Keywords:
Multimorbidity
Mental wellbeing
Social support
Working population
Structural equation modelling
Mediation

A B S T R A C T

This study provides insights into the longitudinal relation between multimorbidity, mental wellbeing, and social support. The analysis used the German Sociomedical Panel of Employees, a study of the German working population aged 40 to 54. In the context of multimorbidity, this population has been little studied.

Multimorbidity is significantly associated with reduced mental wellbeing and social support, whereas social support increases mental wellbeing. We argue that, especially among the working population, multimorbidity reduces perceived social support and decreases mental wellbeing. We elaborate on the mediation process empirically by comparing two distinct structural equation models: a cross-lagged panel mediation model that models a potential reverse-causality between social support and mental wellbeing; and a synchronous mediation model that allows for more immediate mediation.

Both models estimated significant mediation. The relative size of the mediation effect, however, varied widely based on the added mediational paths (8.57% vs. 28%). Fit statistics for both models were good, and the comparison did not favour either model.

We conclude that theoretical reasoning must prevail over empirical testing. The cross-lagged model implies a more longitudinal (lagged) mediation process for social support. However, we suggest an immediate, flexible mediation as more plausible. Nevertheless, we suggest that cross-lagged models, when given a data structure and time gaps, reflect the social processes adequately.

1. Introduction

Given the demographic shifts and accompanying higher morbidity rates in recent years, interest in research on multimorbidity has grown (Tetzlaff, Muschik, Epping, Eberhard, & Geyer, 2017). The combination of ageing societies and increased rates of morbidity has resulted in an increase in health care expenditure (Cassell et al., 2018). On the micro-level, the use of multiple medications by multimorbid individuals leads to increased demands on health care coordination (Crotty, Rowett, Spurling, Giles, & Phillips, 2004). Complex conditions combined with declining physical functioning lead to increased symptom burden (Jindai, Nielson, Vorderstrasse, & Quiñones, 2016), which increases the demands on coping resources. Unmet demands result in reduced health-related quality of life and mental wellbeing (Blinderman, Homel, Billings, Tennstedt, & Portenoy, 2009). The predominantly incurable nature of multimorbidity maintains the adverse effects throughout the life course. Hence, intermediate, tangible factors gain relevancy for coping with multimorbidity (Mercer, Smith, Wyke, O'Dowd, & Watt, 2009). Social factors, such as social support, can provide resources required for the prevention (buffering) of the adverse effects of

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https://doi.org/10.1016/j.ssmph.2021.100744
Received 5 October 2020; Received in revised form 22 January 2021; Accepted 24 January 2021
Available online 28 January 2021
2352-8273/

multimorbidity (Kawachi & Berkman, 2001). At the same time, however, multimorbidity may increase the demands for such resources (Boyd & Fortin, 2010).

Multimorbidity is commonly understood as the presence of multiple, diagnosed chronic diseases (Van den Akker, Buntinx, & Knottnerus, 1996). However, the context and the burden of the chronic diseases can be heterogenous, thus the treatment requirements of the individuals. Most studies on multimorbidity have focused only on the geriatric population. In Germany, however, most people in the age range 50–64 suffer from two to four chronic conditions (Nowossadeck, 2012). This age range also represents the last quarter of working life.

The present study examines the associations between multimorbidity, mental wellbeing, and social support in adults aged 40 to 54. It provides insights into a population that has been little studied. For statistical analysis, we used panel data and applied structural equation models (SEMs) and we try to account for causal precedence, confounding factors, and the longitudinal mediational process. We discuss our results and implications based on the comparison between a synchronous mediation model and a cross-lagged panel model (CLPM) with mediation.

1.1. Theoretical framework

Referring to the theory of “stress appraisal and coping” proposed by Lazarus and Folkman (1984), Cohen and Wills (1985) elaborated on the role of social support. They argued that social support functions as a buffer against stress. Their “buffering hypothesis” states that social resources provide a buffer against the stressful encounter by preventing stress appraisal and enabling reappraisal of the response. Kawachi and Berkman (2001) refined the buffering hypothesis based on life-stages, economic status, and gender. They concluded that more focus on the individual networks and situations is required to account for the dynamics between health and social support.

Regarding the individual networks, the quantity and quality of social ties are a major resource for mental wellbeing. Particularly with complex chronic conditions such as multimorbidity, demands for buffering resources increase to prevent adverse health effects. One such resource is social support. For instance, Kroenke, Kubzansky, Schernhammer, Holmes, and Kawachi (2006) showed that social support increases the survival rate of breast cancer patients. More recently, Olaya et al. (2017) noted an increased survival rate of geriatric multimorbid individuals with high levels of social support.

Social relations affect wellbeing and health through three pathways: psychological, physiological, and behavioural (Berkman, Glass, Brissette, & Seeman, 2000; Kawachi & Berkman, 2001). Recently, Sturmberg, Bennett, Martin, and Picard (2017) discussed the role and interaction of these pathways in a more holistic approach to multimorbidity in which they interlink medical, physiological, psychological, and behavioural mechanisms within the social environment. From such a vantage point, the contributions of Kawachi and Berkman (2001) increasingly gain relevancy. Particularly in the case of multimorbidity, where stress exposure is continuous, the need for buffering resources is also continuous.

1.2. Multimorbidity beyond geriatrics

Few studies have focused on the impact of multimorbidity on mental wellbeing in the context of the working population (Smith et al., 2014; Ubalde-Lopez, Delclos, Gimeno, Calvo-Bonacho, & Benavides, 2014). Investigating multimorbidity beyond the geriatric context is important for two reasons. First, multimorbidity can reduce the ability to work and lead to early retirement or even job loss (Kadijk, van den Heuvel, Ybema, & Leijten, 2019; Sundstrup, Jakobsen, Mortensen, & Andersen, 2017). Second, reduction in the ability to work and job loss are associated with decreasing social ties and adverse effects on the social integration of individuals (Brand, 2015; Darity & Goldsmith, 1996). Social support, again, can be viewed as a resource for maintaining the ability to work (Peters, Spanier, Mohnberg, Radoschewski, & Bethge, 2016). Due to the global trend of raising the retirement age, research on this particular population is of high relevance.

1.3. Multimorbidity, social support and mental wellbeing

Even Cohen and Wills (1985) had encountered difficulties in precisely defining the buffering role of social support. Some researchers have taken social support as a moderator (e.g., Cobb, 1976; Zhou, Zhu, Zhang, & Cai, 2013) and others as a mediator (e.g., Aartsen, Veenstra, & Hansen, 2017; Backe, Patil, Nes, & Clench-Aas, 2018). Moderation means that the effect of the stressor (multimorbidity) on mental wellbeing is a function of social support. Assuming moderation solely also implies that multimorbidity does not affect social support but that the effect of multimorbidity on mental wellbeing is a function of the level of social support (Aiken & West, 1991). In contrast, mediation imposes a process perspective in which changes in the stressor influence the mediator and by that the mediator captures a part of the stressor effect (often called a-path). At the same time, changes in social support influence mental wellbeing (often called b-path) (Baron & Kenny, 1986). Social support thereby mediates (buffers) a proportion of the stress level effect on mental wellbeing. In Fig. 1 we present a conceptual diagram of the mediation process where multimorbidity (X) is the stressor und social support is the mediator (M) and mental wellbeing is the outcome (Y). Fig. 1 also helps in differentiating moderation from mediation because moderation would require the absence of the a-path between multimorbidity and social support. However, we argued that the multimorbidity increases the demands for social support (Lin, Dean, & Ensel, 2013); thus, the presence of the a-path is required. In regard to the effect of multimorbidity on mental wellbeing (c-path), social support may offer both mediation and moderation. This scenario indicates a stress-support interaction and is often referred to as moderated mediation or XM-interaction (MacKinnon, Valente, & Gonzalez; 2020), which means that the portion of the buffered stress effect might change depending on the stress level itself and vice-versa. In Fig. 1 the XM-interaction is depicted with the dashed line (d-path) from M to the c-path.

We argue that, in the working population, multimorbidity reduces the perception of social support due to its adverse effects on the ability to work and social ties. Multimorbidity simultaneously increases the demands for social support. Social support is therefore not a moderator but a mediator of the process of coping with stress. We assume that multimorbidity is negatively associated with social support and mental wellbeing and that social support provides a buffer against the effect of multimorbidity through mediation.

Defining the causal precedence between social support and mental wellbeing is difficult, however. Reduced mental wellbeing in the present may reduce the perception of social support in the future, irrespective of the level of social support provided.

1.4. Confounding factors

Confounding factors affect at least two of the three variables of interest (Pearl, 2009). We differentiate between time-constant and time-varying confounders. We consider the time-constant confounders of sex, educational level, personality traits, and age. The conditions of multimorbidity and mental wellbeing can be stratified by sex. For instance, cardiometabolic diseases are more common in men than in women, whereas women more commonly experience mobility limitations (Prados-Torres, Calderón-Larrañaga, Hancco-Saavedra, Poblador-Plou, & van den Akker, 2014). Women are also more likely than men to experience multimorbidity in combination with depression throughout the life course (Agur, McLean, Hunt, Guthrie, & Mercer, 2016). They also tend to initiate, maintain and provide more supportive social relations than men do (Day & Livingstone, 2003). In cases of low

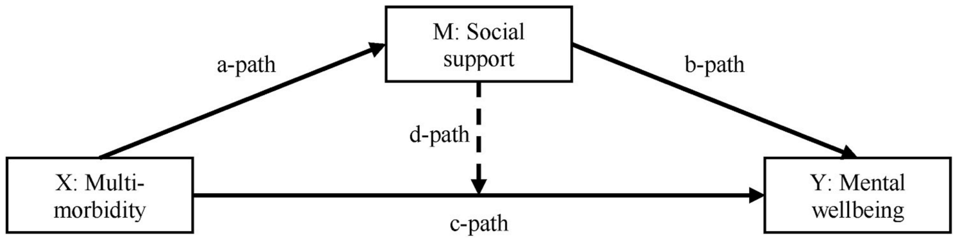

Fig. 1. Conceptual Diagram of mediation model.
Note: Assumption for XM-interaction with mediation depicted as d-path (dashed line).

social support, men have been found to be more vulnerable to depression than woman, especially older adults (Sonnenberg et al., 2013). Higher educational levels and socioeconomic status are associated with different patterns of health behaviour, social networks and wellbeing (Pinquart & Sörensen, 2000). Personality traits partly shape the influence of social support on mental wellbeing. For instance, extraversion increases the risk of depression in older adults and changes their perception of social support (Peerenboom, Collard, Naarding, & Comijs, 2015). We consider job loss as a confounder for social support and mental wellbeing. Partnership status and changes in the partnership may reduce social support and mental wellbeing (Bolger, Zuckerman, & Kessler, 2000; Thoits, 2011).

2. Material and operationalisation

2.1. Data

For analysis purposes, we used the Third German Sociomedical Panel of Employees (GSPE-III) (Bethge, Spanier, Neugebauer, Mohnberg, & Radoschewski, 2015). The GSPE-III started in 2013 and is an ongoing large-scale cohort study. The participants are drawn randomly from the register of the Federal German Pension Insurance Agency. The survey sample consists of 10,000 employees aged between 40 and 54 who have previously received sickness benefits. Men and women are represented equally in the sample. The study consists of three postal surveys. The first wave started in 2013. Follow-up surveys were conducted in 2015 and 2017. Eligible for follow-up were baseline participants who consented for the survey in 2015 and 2017. The dataset's primary purpose is to identify factors affecting the ability to work and early retirement in workers with health impairments.

All three waves measured indicators of mental wellbeing, social support, and existing diseases. The dataset is well suited for the research question for three reasons. First, it allows multimorbidity to be identified among the working population at three points in time. Second, the dataset includes coherent measures of mental wellbeing and social support. Third, the longitudinal design allows for the investigation of mediational processes.

This study has been approved by the ethics committee at Hannover Medical School and the data protection commissioner of the German Pension Insurance Agency.

2.2. Measurements: multimorbidity

Respondents declared the diseases that a doctor had diagnosed them with. Applicable conditions were coded as 1, non-applicable as 0. We then created a morbidity sum-score. We defined a binary measurement of multimorbidity with morbidity sum-score values higher than 2 represent multimorbidity; values lower than 2 represent non-multimorbidity. This is a more restrictive definition than those used by most researchers (see Diederichs, Berger, & Bartels, 2011; Willadsen et al., 2016). The main reason is that our sample was characterised by individuals who previously had received sickness benefit. Moreover, this definition clearly distinguishes between comorbidity and multimorbidity and is commonly used in Germany (Van den Bussche et al., 2011).

Generally, multimorbidity is a complex phenomenon. We aimed at reducing unintended heterogeneity where logical. We limited the applicability of each disease for multimorbidity to a specific set. These limitations for the conditions are chronic, severe, and somatic. Hence, we coded mental disorders (not somatic), cancer (non-chronic), and back pain (not severe) as 0 on the morbidity sum-score. However, we did not necessarily exclude individuals with these conditions from the multimorbidity measure. We treated individuals with morbidity sum-scores greater than 2 as multimorbid irrespective of their other conditions. Table 1 presents a more detailed description of the diseases counted in the morbidity sum-score.

2.2.1. Measurements: social support

Perceived social support was measured using the Oslo-3 Social Support Scale (Dalgard, Bjørk, & Tambs, 1995), a commonly used assessment in European public health research. The scale consists of three items, each capturing different aspects of social support. The index of these items ranges from 3 to 14 and can be categorized into low (3–8), moderate (9–11) and high social support (12–14).

2.2.2. Measurements: mental wellbeing

Mental wellbeing was measured using the mental health sub-scale of the Short-Form 36-Item Health Survey (SF-36) (Ware & Sherbourne, 1992). The SF-36 is a validated questionnaire widely used to measure

Table 1
Overview of measurements used in data analysis.

Multimorbidity (X)	Measurement Level
Morbidities	Binary
Cardiovascular	
Respiratory	
Neurological/Nervous	
Digestive	
Urogenital	
Skin Diseases	
Hormone/Metabolic	
Blood-Related	
Congenital	
Other Ailments	
Morbidity-Sum-Score	Metric
Mediator (M)	
Oslo-3 Social Support Scale	Metric/Categorized
Outcome (Y)	
SF-36 Mental Health Subscale	Metric
Covariates (C)	
Time-Constant	
Highest Educational Attainment	Categorical
Sex	Binary
Year of Birth	Metric
Extraversion (Big-Five)	Metric
Time-Varying	
Smoking Status	Categorical
Partnership Status	Binary
Employment Status	Binary

Note Multimorbidity = Morbidity-Sum-Score >2.

health-related quality of life. The five mental health subscale items measure different aspects of mental health, such as depression, anxiety, general positivity, and emotional and behavioural control. The summarised score of these items varies between 0 and 100, with 100 indicating the highest level of mental health.

2.2.3. Measurements: confounders

We tried to account for the main confounding variables discussed in section 1.4. We divided the set of confounding variables into time-constant and time-varying confounders. We measured the following time-constant confounders: sex (binary), age (continuous), highest educational attainment (categorical), and extraversion (continuous). The extraversion measure consisted of three items from the Big Five Inventory-Short subscale (Lang, John, Lüdtke, Schupp, & Wagner, 2011). We measured the following time-varying confounders: smoking (categorical), partnership status (binary), and employment status (binary). We considered these covariates to be the most relevant confounding factors.

3. Statistical analysis

3.1. Structural equational models and longitudinal mediation

This study examined the relations between multimorbidity, social support, and mental wellbeing. We translated the theoretical implications into SEMs, guided by Cole and Maxwell's (2003) and MacKinnon's (2008) recommendations. SEMs are a highly flexible tool and adaptable to mediational processes. Before applying the SEMs, we checked the basic requirements of mediation by inspecting the path coefficients, following Baron and Kenny (1986). We further checked for XM-interaction between multimorbidity and social support depicted as d-path in Fig. 1.

The SEMs depicted in Figs. 2 and 3 consist of five elements: (1) the measurements, (2) the autoregressive parts, (3) the bidirectional (co-varying) paths, (4) the cross-lagged paths and (5) the cross-sectional paths. First, the measurements shown in Figs. 2 and 3 are manifest (1); latent variables were not used. Given the problems related to measurement invariance, using manifest variables is reasonable. Second, the autoregressive part (2) accounts for the fact that the previous state of a measurement predicts the current state. Third, the bidirectional (co-varying) paths calculate shared variances (3), meaning that there are no directional associations in the cross-sections. This is especially important during the first wave of observation (baseline) to account for pre-existing differences in the relation between the measurements. Fourth, the cross-lagged paths (4) define the structure and the time-span of the relations. After imposing autoregressive and co-varying paths, the cross-lagged paths can then estimate the change in a measurement while controlling for prior associations. Fifth, the cross-sectional paths (5) partly control for the cross-sectional associations between the measurements.

For both models, we calculated relevant effects using the coefficient-product method (Bollen, 1987). The effect of primary interest is the overall indirect effect (OIE), which expresses the degree to which mediation is empirically observable and equals the sum of all indirect effects. The overall total effect (OTE) is the sum of all possible pathways, shown as coefficient-products. The overall direct effect (ODE) is the product of all direct paths (including autoregressive paths) from multimorbidity to mental wellbeing.

To calculate confidence interval calculation of the effects, we performed a bootstrapping procedure with 10,000 iterations. The models were based on maximum likelihood (ML) estimation without the inclusion of missing values. Hence, the "missing completely at random" assumption holds. Despite the addition of categorical measurements, we did not apply asymptotically distribution-free estimation methods, because the sample size was less than 2000 (Boomsma & Hoogland, 2001; Browne, 1984). Moreover, model misspecification, sensitivity, and convergence conflicts are issues with these methods (Finney & DiStefano). However, we adjusted the standard errors for the non-normal distribution of data using Satorra and Bentler (1994) adjustment. We included time-constant covariates at t0, each with cross-sectional paths on the primary measurements. Similarly, we added time-varying covariates with a t-1 lag, starting at t1. We set each time-varying covariate as autoregressive to itself, using the previous states to predict current states.

Beyond these technical implications, SEMs require well reasoning. SEMs require even more reasoning in longitudinal mediational settings because of increased possibilities and complexities in the model specification (Cole & Maxwell, 2003). We present two distinct SEM models that try to address different theoretical implications according to their empirical translation.

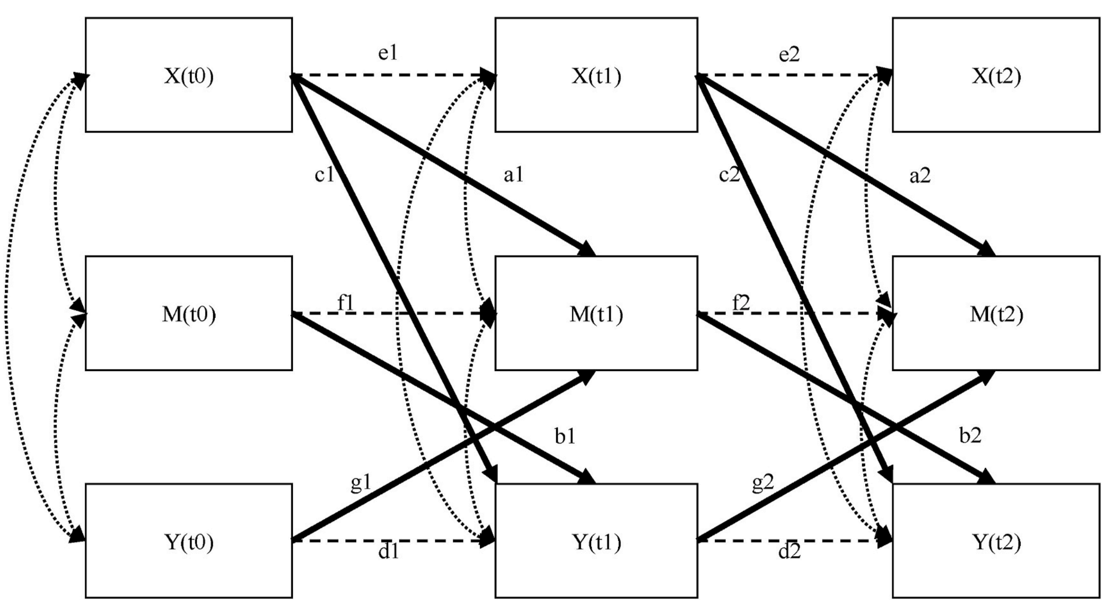

Fig. 2. Cross-lagged panel model (CLPM) with mediation.
Note: (1) Boxes = measurements; (2) Slashed paths = autoregressive (3) Curved paths = co-varying; (4) Bolt paths = cross-lagged. Error-terms and covariates omitted for visualization purposes.

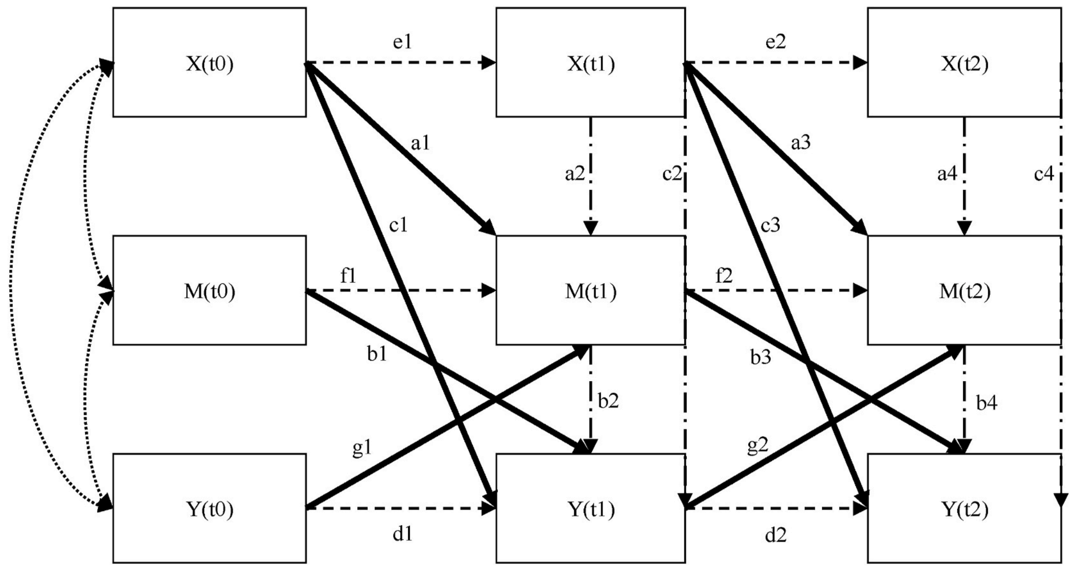

Fig. 3. Synchronous mediation model.
Note: (1) Boxes = measurements; (2) Slashed paths = autoregressive (3) Curved paths = co-varying; (4) Bolt paths = cross-lagged (5) Slash-pointed paths = Cross-sectional. Error-terms and covariates omitted for visualization purposes.

3.2. SEM I: cross-lagged panel model with mediation

The first model (Fig. 2) imposes restrictive assumptions in the cross-sections to account for a potential alternative causal precedence between social support and mental wellbeing. We applied a version of a cross-lagged panel model that has been extended for longitudinal mediation (Newsom, 2015; Selig & Preacher, 2009). By imposing cross-lagged paths between mediator and outcome, this model empirically adjusts for the alternative temporal precedence between social support and mental wellbeing (Finkel, 1995) and accounts for Granger causality (Granger, 1969).

Despite the benefits of the CLPM, it imposes substantial restrictions on the lag between the effects. Deciding on the temporal lag is not trivial, because the temporal lag defines the causal process in its core (Gallob & Reichardt, 1991). We assumed that the temporal lag, given by the panel waves, is correctly specified in the CLPM.

3.2. SEM II: synchronous mediation model

Social processes and the influence on mental wellbeing can be immediate and flexible. With this in mind, we also estimated an alternative model to the CLPM, which allows for more contemporary (within-wave) effects. This model assumes that social support precedes mental wellbeing, allowing for cross-sectional effects. Fig. 3 depicts a model that is a variation of MacKinnon's (2008) "Autoregressive Model III" (2008: 204–206). The major difference between the models in Figs. 2 and 3 is that the second model imposes directional paths that allow for the calculation of cross-lagged effects and cross-sectional effects adjusted by the autoregressive part. The cross-lagged path adjusts for the effect of mental wellbeing on social support. Simultaneously, the additional paths increase the complexity of the model and impose stronger assumptions on the theoretical model, because it does not explicitly account for the Granger causality issue between social support and mental wellbeing.

4. Results

4.1. Descriptive statistics

Fig. 4 presents the attrition from the study population to the analysis population. The baseline sample (n = 3294) decreased by 36% at t2 to a total of 2108 cases. After case-wise deletion of missing values of the analysis measurements, this population fell by an additional 21%, resulting in a final analysis sample of 1675 respondents. Table 2 compares the full sample (any valid entry) with the restricted sample (n = 1675) to account for the "missing completely at random" assumption. We observed no systematic differences in the measurements between the samples.

The results presented in Table 3 met the requirements for mediation analysis. Multimorbidity is significantly associated with social support (a-path) and mental wellbeing (c-path), and social support is significantly associated with mental wellbeing (b-path). The total effect (a $\times$ b + c) is approximately one-fourth to one-third higher than the direct effect (a-path). We also tested for XM-interaction by adding interaction terms between multimorbidity and social support (d-path) for each wave, but we found no significant interactions. Hence, we excluded interactions from the final models. The path products (a $\times$ b $\times$ c) are significant and show in the opposite direction, which indicates complementary/partial mediation (Zhao, Lynch, & Chen, 2010).

Tables 4 and 5 correspond to the SEMs depicted in Figs. 2 and 3, respectively. Each table compares the main statistical measures with and without the addition of covariates. For each model, effects were calculated by the coefficient-product method using standardized coefficients. For a comprehensive overview, we also included the formulas based on the paths of the corresponding figures. Based on standard error calculation with Satorra and Bentler's adjustment (1994), we chose appropriate summary and fit statistics with the comparative fit index (CFI), root mean square error approximation (RMSEA), and the coefficient of determination (CD).

4.2. Cross-lagged panel model with mediation

The CLPM has only one mediational path, from a1 to b2 (Fig. 2). Results from the CLPM indicate significant effects for ODE, OIE, and OTE, irrespective of covariate addition. In both models, the relative size of OIE on the OTE is about 8.57%. Adding covariates improved the fit statistics. Doing so mostly affected the RMSEA, which reduced from 0.131 to 0.061. The CFI indicated a good model fit regardless of covariate addition (CFI = 0.923 to CFI = 0.942).

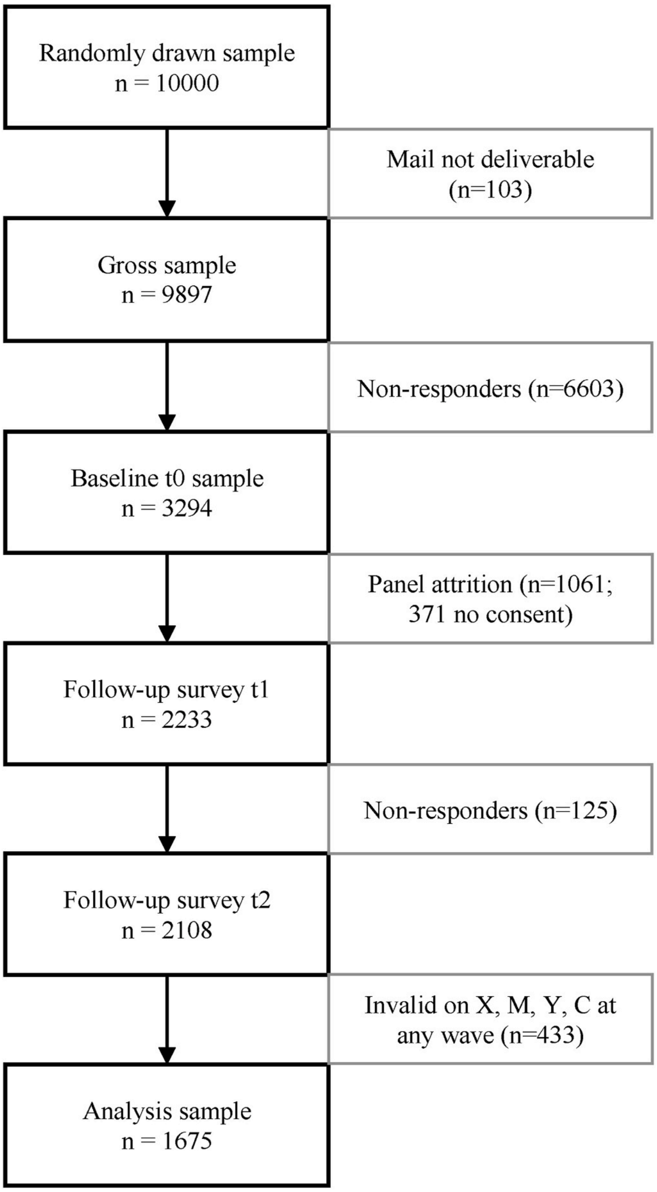

Fig. 4. Flow chart of the Third German Sociomedical Panel of Employees including analysis sample restriction.

4.3. Synchronous mediation model

The increased contingency in the synchronous mediation model added by the cross-sectional paths required a more detailed effect calculation. Numerous wave-specific effects could be calculated. The effect calculation was based on the respective path-products starting from multimorbidity at t0. This model also indicates significant effects for ODE, OIE and OTE. The effect sizes increased, but the proportion of the OTE accounted for by the OIE (25.7%) rose sharply compared to that of the CLPM (8.57%). After covariate inclusion, the proportion was about 2.2 percentage points higher. Similarly to the CLPM, the halved after covariate inclusion (0.131–0.068). Again, CFI also indicated a good model fit irrespective of covariate inclusion (CFI = 0.923 to CFI = 0.951).

Table 2
Descriptive statistics. Comparison of respondents between samples.

Measurements	Full Samples			Restricted-Sample		
	Mean	SD	N	Mean	SD	N
Sex (1 = Female)	0.53	–	3294	0.55	–	1675
Education (categorical)	0.98	0.64	3273	1.02	0.62	1675
Low			699			282
Average			1924			1019
High			650			374
Age at t0	47.93	4.10	3294	48.07	4.01	1675
Extraversion (3-21)	14.72	3.62	3257	14.75	3.59	1675
MWB t0 (0–100)	63.47	21.62	3241	65.24	20.60	1675
SoSu t0 (3–14)	9.52	2.30	3241	9.69	2.24	1675
Morbidity t0 (1–9)	1.19	1.30	3241	1.19	1.28	1675
Multimorbidity t0	0.14		3294	0.14		1675
MWB t1(0–100)	63.63	21.34	2193	64.82	20.54	1675
SoSu t1(3–14)	10.14	2.32	2193	10.22	2.27	1675
Morbidity t1 (1–9)	1.27	1.30	2193	1.24	1.29	1675
Multimorbidity t1	0.15		2233	0.14		1675
MWB t2(0–100)	63.08	20.86	2065	63.54	20.84	1675
SoSu t2 (3–14)	9.88	2.30	2065	9.93	2.31	1675
Morbidity t2 (1–9)	1.38	1.36	2065	1.39	1.39	1675
Multimorbidity t2	0.17		2108	0.17		1675

Note: MWB = SF-36 mental wellbeing; SoSu = Oslo-3 social support.
Full samples information based only on valid entries of a respondent at the specific measurement.

Table 3
Naïve inspection for mediation.

Paths/effects at time-points	T0	T1	T2
a - multimorbidity on social support	−0.929***	−1.002***	−1.058***
b - social support on mental wellbeing	3.409***	3.621***	3.425***
c - multimorbidity on mental wellbeing	−8.643***	−11.584***	−8.852***
Indirect path = a*b	−3.167***	−3.627***	−3.624***
Total effect = (a*b) + c	−11.811***	−15.211***	−12.476***
Path product = a*b*c	27.375***	42.013***	32.079***
XM-interaction: multimorbidity x social support (d-path)	−0.256	0.210	0.253

Note: ***p < 0.001; coefficients for path products obtained by bootstrapping procedure with 1.000 iterations. No significant interactions between multimorbidity and social support indicated. No covariates added.

5. Discussion

5.1. Summary of results

The sample consisted of members of Germany's older working population in whom multimorbidity was identifiable. Generalizability, therefore, seems limited. This limitation was intentional, however, because this analysis examines a population that has been little studied. We modelled longitudinal relations based on a theoretical framework mainly rooted in contributions by Lazarus and Folkman (1984), Cohen and Wills (1985), and Kawachi and Berkman (2001). More precisely, we investigated the buffering hypothesis in the context of multimorbidity, social support, and mental wellbeing. We found consistent associations, multimorbidity decreases social support and mental wellbeing while social support increases mental wellbeing. We further modelled these associations in a longitudinal mediational setting, using various theoretical assumptions. In all our models, we found significant mediation supporting the buffering hypothesis. The size of the mediation effect differed depending on the model.

5.2. Interpretation

Our analysis emphasises the mediating role of social support. We

Table 4
Standardized estimates of cross-lagged panel model with and without covariates.

Effect	Path-products:	Without Covariates			With Covariates		
		Beta	Std. Error	p-value	Beta	Std. Error	p-value
ODE	[c1*d2] +[e1*c1]	−0.064	0.015	0.000	−0.064	0.014	0.000
OIE	[a1*b2]	−0.006	0.002	0.007	−0.006	0.002	0.007
OTE	[ODE]+[OIE]	−0.070	0.015	0.000	−0.070	0.015	0.000
Fit Statistics	Chi^2 Model vs. saturated	df = 13; chi^2 = 389.291			df = 97; chi^2 = 691.740		
	RMSEA	0.131			0.061		
	CFI	0.923			0.942		
	CD	0.727			0.956		

Note: Model computed with maximum likelihood procedure without the inclusion of missing values. Satorra and Bentler (1994) standard error adjustment for the non-normal distribution of data. Path-products correspond to depicted paths in Fig. 2.

showed that multimorbidity reduces social support and mental wellbeing, whereas social support increases mental wellbeing. We tested these findings empirically by comparing two distinct SEMs. The reason for CLPM was to explicitly model for causal precedence between the measurements. However, the CLPM imposed a gap of t+1 between each measurement. This gap reduces the varieties of observable mediations. The CLPM assumes that the imposed time gaps align with social processes. In the given data structure, each wave has a lag of two years, resulting in a total timeframe of four years for the mediation to occur. Due to the dynamic nature of social processes, this restriction seems inappropriate. Nevertheless, the CLPM allowed us to account for uncertainty in the causal process between social support and mental wellbeing. Both factors, the dynamic nature of social processes and modelling for causal precedence, reduce proportion mediated. The first factor might underestimate the potential mediation due to fading associations over the time-lapses. The latter reduces the overestimation of the mediational effect, because it adjusts for a potential reverse-causality. The CLPM estimated a significant OIE that accounts for 8.57% of the OTE.

We defined the mediation process as complementary and as distal because the a-path associations are weaker than the b-path associations (Hoyle & Kenny, 1999). Reconsidering the theoretical arguments given in section 1.3, we think it seems logical that the a-path is weaker due to heterogeneous social settings. Especially when additional lags were imposed by the CLPM between the measurements, the social settings could change in unmeasured ways.

The model in Fig. 3 implies more direct processes than the CLPM. The results indicate a relatively stark, significant mediation, which accounts for approximately 28% of the OTE. The a-paths of Table 3 also show a significant association in the cross-sections. These results give reason for a more contemporary setting in which the mediation takes place within the cross-section. However, despite imposing the g-paths (t-1 mental wellbeing to t1 social support), this model does not explicitly account for Granger causality, leading to potentially overestimated b-paths.

In both models, adding covariates did not lead to fundamental differences. Moreover, both models had a good fit without the inclusion of covariates. Only the CD increased naturally with the addition of covariates.

5.3. Strengths and limitations

Recent investigations into multimorbidity and health disparities in later life provide essential insights into the social determinants (e.g., Singer, Green, Rowe, Ben-Shlomo, & Morrissey, 2019; Torres, Rizzo, & Wong, 2018). From their findings, it seems reasonable to regard multimorbidity as the accumulation of cell damages acquired throughout the life course (Austad, 2016). The social environment partly causes or intensifies these damages (Marengoni et al., 2011; Ward-Caviness et al., 2020). A feedback loop between the manifestation of multimorbidity and the social environment is therefore plausible. Yet, such processes are much more prolonged than the available four-year timeframe of the data.

We argued that social support is a mediator, not a moderator. Social support's role, however, is presumably complex, because it could also be desideratum of a complex interplay between personality traits and the social environment. Hence, alternative explanations, such as the esteem-threat hypothesis (Nadler & Fisher, 1986), are also plausible. The esteem-threat hypothesis predicts an increased level of stress after receiving social support, depending on the individual's personality type. Consequently, personality may confound the association between social support and mental wellbeing (b-path) and moderate the association between multimorbidity and social support (a-path).

In regard to gender differences, women report more mental disorders across all socioeconomic levels (Allen, Balfour, Bell, & Marmot, 2014). Future investigations should consider potential intersections in the tripartite association between multimorbidity, social support and mental wellbeing. For instance, the sensitivity towards the buffering effect of social support could change under certain combinations of gender, ethnicity and socioeconomic status (e.g., Rosenfield, 2012). Such an analysis would require more focus on individual traits, contexts and social networks, which could not be addressed in the current analysis.

The data did not clearly distinguish between multimorbid and healthy individuals, because the selection criterion of the sample was that individuals had previously received sickness benefits. This selection could contribute to an underestimation of the effects in general. We therefore proposed a restrictive definition of multimorbidity that distinguished between morbid and multimorbid individuals. The use of a binary indicator of multimorbidity, however, is contentious. Although conceptually adequate, it categorises heterogeneous individuals into the same categories. Future research on multimorbidity should consider different types of multimorbidity. Multimorbidity could then be regarded as the combinatory interplay between different disease profiles, instead of the count of individual diseases. For instance, Wei, Kawachi, Okereke, and Mukamal (2016) validated a weighted measure for multimorbidity based on the SF-36 physical functioning subscale. Such measures could capture more of the mediational process, as certain types of diseases are associated with higher support demands. Unfortunately, consistent information on the SF-36 physical function subscale was unavailable.

By presenting two distinct SEMs we provided alternative modelling based on the different theoretical implications of the Granger causality and the mediational process. Other empirical strategies to investigate longitudinal mediation, such as marginal structural models with inverse probability weighting, are also valid and have certain advantages

Table 5
Standardized estimates of synchronous mediation model with and without covariates.

Effect	Path-products:	Without Covariates			With Covariates		
		Beta	Std. Error	p-value	Beta	Std. Error	p-value
ODE	[c1*d2] + [e1*c3] + [e1*e2*c4] + [e1*c2*d2]	−0.052	0.015	0.000	−0.049	0.014	0.000
OIE	[a1*c3] + [a1*b2*d2] + [a1*f2*b4] + [a1*b2*g2*b4] + [e1*a2*b3] + [e1*a2*b2*d2] + [e1*a2*f2*b4] + [e1*e2*a4*b4] + [e1*a2*b2*g2*b4]	−0.018	0.005	0.001	−0.019	0.005	0.000
OTE	[ODE]+[OIE]	−0.070	0.015	0.000	−0.068	0.015	0.000
Fit Statistics	Chi^2 Model vs saturated	df = 13 $chi^2 = 389.291$			df = 64 $chi^2 = 562.483$		
	RMSEA	0.131			0.068		
	CFI	0.923			0.951		
	CD	0.727			0.958		

Note. Model computed with maximum likelihood procedure without the inclusion of missing values. Satorra and Bentler (1994) standard error adjustment for the non-normal distribution of data. Path-products correspond to depicted paths in Fig. 3.

concerning exposure-induced mediator-outcome confounding and XM-interactions (VanderWeele, 2016; VanderWeele & Tchetgen Tchetgen, 2017). Nevertheless, the SEM approach allowed us to model the temporal relation between social support and mental wellbeing and compare the results across the models.

Despite the benefits of empirical modelling for causal precedence, the lags imposed by the CLPM are unsuitable for the dynamic process with the given data structure. A CLPM based on shorter time intervals between the measurements could yield different results. We support the use of the CLPM with appropriately structured data. Given a dataset with intervals of two years, however, we favour the synchronous mediation model, depicted in Fig. 3, despite its high complexity. Our findings illustrate that theoretical reasoning must prevail over the empirical modelling.

Because social support is tangible by interventions, our results are of practical relevance for interventions that aim to stabilise or increase mental wellbeing in the older working population. As suggested by Sturmberg et al. (2017), multimorbidity is a result of interconnected physiological and social processes; therefore, health professionals should also consider the individual and social resources when planning multimorbidity interventions. Our results suggest that social support helps in maintaining mental wellbeing despite the presence of multimorbidity. In addition to the benefits of increased mental wellbeing, previous research has suggested that social support slows the progression of morbidities and prevents mortality in multimorbid populations (Schäfer et al., 2019; Olaya et al., 2017). Furthermore, social support and mental wellbeing positively affect the ability to work and return-to-work rates (Peters, Spanier, Radoschewski, & Bethge, 2018; Brouwer et al., 2010). We believe that increasing social support to maintain mental wellbeing is a viable strategy in the comprehensive treatment of multimorbidity in the older working population.

Ethics statement

We acknowledge the ethical standards in publishing our research regarding authorship, originality and plagiarism, data access and retention, multiple, redundant or concurrent publications, acknowledgement of sources, disclosure and conflicts of interest, fundamental errors in published work, and reporting standards.

Funding

The utilized data in this article (GSPE-III) was founded by the “German Pension Insurance Union”(Deutsche Rentenversicherung Bund). However, the research itself did not receive any specific grants from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Ibrahim Demirer: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Visualization. **Matthias Bethge:** Conceptualization, Methodology, Writing - review & editing, Data curation. **Karla Spyra:** Writing - review & editing, Data curation. **Ute Karbach:** Conceptualization, theoretical framework, Writing - review & editing. **Holger Pfaff:** Conceptualization, Writing - review & editing, PhD supervisor.

Declaration of competing interest

None.

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