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Anti-aging: How innovation is shaped by firm age and mutual knowledge creation in an alliance

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ABSTRACT

Firms might operate in alliances and 'vitalize' themselves to achieve innovation. Still, the older and more mature firms might may not sufficiently utilize the innovation potentials in alliances because they have structural rigidities, and their managers continuously draw upon established sensemaking patterns. Our hypotheses testing on a sample of 296 firms in alliances finds that greater firm age decreases the possibilities for innovation value creation. While all firms across the age range can benefit from mutual knowledge creation in their alliances, the older firms can reduce their limitations for innovation value creation when they mutually create knowledge with their partners. Our study contributes explicitly to the dynamic relational view, combining it with a sensemaking theory.

1. Introduction

Innovation demands creative expertise, knowledge, and learning processes among diverse persons from different functional areas and hierarchical levels (Anzola-Román, Bayona-Sáez, & García-Marco, 2018). Put forward by the *dynamic relational view* (Dyer & Singh, 1998; Dyer, Singh, & Hesterly, 2018; Mesquita, Anand, & Brush, 2008; Weber, Bauke, & Raibulet, 2016), firms might improve value creation in product innovation in particular by using complementarities provided by inter-firm alliances (Bouncken & Kraus, 2013). Still, when pursuing innovation through alliances, firms need to understand and interpret their partners' decisions, actions, and motives and use the flow of knowledge in the alliance (Narayandas & Rangan, 2004; Bouncken & Fredrich, 2016).

Presumably, innovation is facilitated through the open flow of ideas moving across inside and outside firm boundaries, and this seems more accessible for firms that are, or remain, more 'juvenile' compared to the often more rigid 'aging' firms. The main reason for this is that firms usually develop more rigid structures during their life cycle and have internal communication deficiencies (BarNir, Gallaugher, & Auger, 2003; Teichert & Bouncken, 2011). Somewhat related to this, is the older or more mature firms become, the greater the tendency for managers to develop specific and relatively stable sensemaking processes that continuously guide their attention and interpretation processes. Hence, older firms will less likely pay attention to information and knowledge that do not fit into their conventional sensemaking patterns and thus find themselves in a position that limits their innovation value creation (Foss, Jeppesen, & Rullani, 2020; Ocasio & Joseph, 2018). Thus, the question arises whether older firms can facilitate innovation by operating with more juvenile firms.

At first sight, the complementarities, trust, and the learning from another firm in the alliance might support innovation for all firms, including the older firms (Eggers, Kraus, & Covin, 2014; Thorgren & Wincent, 2011). However, at second sight, even when operating in an alliance, older firms might find it more challenging to draw on the inflow and outflow of ideas and knowledge among firms. It might be because older firms already have established sensemaking patterns and continuously draw upon them, even when operating in an alliance. These patterns render them less adaptive to new information or creative ideas that would otherwise stimulate innovation. Hence, we assume that older firms might find it more challenging to create innovation value, even when operating in an alliance that offers complementarities for innovation. However, how can older firms work against their established sensemaking patterns in alliances that even restrict them from learning from their partner?

The current paper investigated this question and built our research purpose. We first create a theoretical model and then tested it empirically. We develop our model and the argumentation for our hypotheses by combining the dynamic relational view with the sensemaking perspective (Hill & Levenhagen, 1995; Seidl & Werle, 2018; Wright, Manning, Farmer, & Gilbreath, 2000). We first hypothesize that firms

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can realize less innovation value in alliances when they are relatively old because the older firms have more rigid processes and sensemaking patterns. Second, we hypothesize that mutual knowledge creation brings novel synergies, perhaps even serendipitous ideas, that improve value in innovation (Bouncken, Hughes, Ratzmann, Cesinger, & Pesch, 2020c). Mutual knowledge creation includes moving away from overly rigid sensemaking patterns. It activates surface and deep-level knowledge creation processes among firms. We assume those advantages, even if a high level of mutual knowledge is present, which could indicate high levels of overlapping knowledge. The high levels of overlapping knowledge among firms might limit their ability to use their differences as complementarities for innovation. Thus, we hypothesize a positive but diminishing effect of high levels of mutual knowledge creation on innovation. Third, we hypothesize that older firms might create their 'anti-aging' recipe by venturing into the mutual knowledge creation in the alliance. The gradual adaptations in creating mutual knowledge occur repeatedly and recursively within surface-and deep-level processes among managers in the alliance. The newly developed mental frames substitute and change existing patterns and so dissolve rigid sensemaking patterns. Thus, in particular, the older firms might improve innovation and overcome aging by being open to exchanges through mutual knowledge creation in alliances.

Our hypotheses were tested by a sample of 296 firms in the manufacturing sector with major operations in Europe, using the latent moderated structural equations (LMS) approach to data analysis. Our results indicated a negative slope between firm age and innovation value creation in alliances. Findings also show that mutual knowledge creation positively affects innovation value creation in alliances across the full range of firm age. The positive effects diminish at high levels of mutual knowledge creation. In particular, the older firms can compensate for their negative effects by rigidities and overly repeated similar sensemaking processes on innovation value by a mutual knowledge creation in the alliance.

Our findings theoretically contribute to the dynamic relational view of the understanding that firm age might limit innovation even when firms operate in alliances. Complementarities for innovation demand more attention, openness, permeability, and flexibility prevalent in mutual knowledge creation among firms (Foss et al., 2020; Ocasio & Joseph, 2018). Methodically, our study suggests a novel approach to testing and working for biases related to causal inference.

2. Theoretical background

To study how older firms in particular can improve their innovation outcomes by allying with more juvenile firms, we applied the dynamic relational view with sensemaking processes in alliances. The dynamic relational view is about learning processes in alliances. It allows us to consider changes and learning among firms and, in particular, the learning that can occur through sensemaking processes in firms that guide the development of mutually new knowledge. This knowledge might allow older firms to achieve anti-aging benefits from their more juvenile alliance partners. Hence, our conceptual framework is based on the dynamic relational view and mutual knowledge theory.

2.1. Dynamic relational view and sensemaking in alliances

Inter-organizational alliances are commonly defined as voluntary, relatively long-term, cooperative agreements formed by two or more organizations (Bruyaka, Philippe, & Castañer, 2018; Das & Teng, 2002; Gulati, 1998). The relational view (RV) has shown that repeated, continued ties or strong ties significantly impact complementarities and alliance performance (Dyer & Singh, 1998; Dyer et al., 2018; Mesquita et al., 2008; Weber et al., 2016). The interactions or relational continuance among firms in the alliance can improve social processes, partner-specific absorptive capacity, and learning (Dyer & Hatch, 2006; Dyer & Singh, 1998; Fredrich, Bouncken, & Kraus, 2019). According to the dynamic relational view, complementarities increase when firms take on strong relationships towards learning processes among firms (Dyer & Singh, 1998; Dyer et al., 2018; Mesquita et al., 2008; Weber et al., 2016).

When applied for innovation, the knowledge must be processed, understood, and made sense of within and among firms (Bouncken et al., 2020c). Hence, innovation processes demand the exchange and understanding of ideas and knowledge, allowing diverse perspectives and knowledge combinations (Covin et al., 2020). Because the pursuit of innovative products generally challenges taken-for-granted assumptions, approaches, and routines, organizational members need to interpret information in a broader context and adjust the action to the context (Dougherty, Borrelli, Munir, & O'Sullivan, 2000). Individuals from different levels and organizations influence product innovation in multiple ways, having different interpretations of technologies, components of the product, rules in the process, objectives, and the market (Christiansen & Varnes, 2009; West & Bogers, 2014). The sensemaking perspective (Weick, 1995) offers explanations for the construction of meaning in organizations. Sensemaking is an "ongoing accomplishment that emerges from efforts to create order and make retrospective sense of what occurs" (Weick, 1993, p. 635). To make sense of new foci or directions for innovation, organizational members may reach out to others in their firm but with others in collaborating firms (Seidl & Werle, 2018). Different firms will have different patterns of what makes sense and thus have different or even incompatible perspectives (Drazin, Glynn, & Kazanjian, 1999).

However, managers in firms will have developed specific and stable ways to make sense of issues and how to interpret situations. When a firm operates with well-approved and established processes, roles, and structures, there will be minor variance in what makes sense. Even when the specific individuals who interact in the alliance, between firms, do change, there might be stable behavior patterns and interpretation systems embedded in the established structures. These rigidities explain why older firms often have problems with creating value from innovation. Older firms might increase exchanges inside and outside the organization to stimulate innovation. However, when their structures and paths remain, change and innovation might still be somewhat slower than in more juvenile firms with more porous boundaries. Instead, older or more mature firms might reproduce their sensemaking patterns embedded in established structures. The somewhat rigid patterns might endure when firms are operating in an alliance. Although alliances might provide some stimuli for changing sensemaking patterns, older firms might still be locked in by their established patterns (Bouncken, Fredrich, Kraus, & Ritala, 2020b). Even learning from the younger firms might concentrate on single-loop learning processes, just re-enforcing the patterns.

Hence, we posit that older firms, compared to younger firms, will be less effective in creating innovation value, even though innovation becomes fueled when different firms engage in sensemaking of different knowledge stocks, technology, and interests (Griffith, 1999). Some of the contradicting or different logics of the firms might be reframed and rebound into conventional interpretations on the firm level. Hence, even if innovation generally benefits complementarities, the established sensemaking patterns and rigidities in older firms will hinder the creation of innovation value.

H1: Innovation value creation will decrease when firms become older.

2.2. Mutual knowledge creation

Product innovation benefits from mutual knowledge creation between firms in alliances that connect, breed, overlap, and merge knowledge of the entities towards novel outcomes (Roy, Sivakumar, & Wilkinson, 2004). Mutual knowledge can consist of a shared understanding of reality and compatible, shared principles for routines, rules, or problem-solving processes within the alliance (Fang & Zou, 2010). Mutual knowledge creation is investigated in research on the team, organizational, and inter-firm levels (Brown, Lusch, & Nicholson, 1995;

Table 1
Latent Variables with Indicator Statistics and Results of Confirmatory Factor Analysis (CFA) using Robust Maximum Likelihood Estimator (MLR) with $n = 296$.

Constructs	Indicators	M	SD	SK	KT	FL	CR	AVE	FLR	HTMT
Mutual knowledge creation (MKC)	We *mutually* develop novel ideas/ insights/ products etc. *with our partner*.	3.302	1.477	−0.413	−0.722	0.858	0.892	0.735	0.459	0.537
	We *mutually* find novel solutions by sharing knowledge *with our partner*.	3.274	1.297	−0.331	−0.593	0.933				
	We share and merge knowledge *with our partner* to accomplish new projects successfully.	3.438	1.312	−0.358	−0.595	0.773				
Innovation value creation (IVC)	How much value does the relationship generate in the following fields?						0.877	0.705	0.479	0.537
	…new products incorporating technology new to customers.	3.379	1.394	−0.475	−0.661	0.882				
	… new products offering benefits new to the customers.	3.596	1.116	−0.676	0.094	0.821				
	… new products that introduce many completely new features to the market.	3.263	1.431	−0.236	−0.808	0.812				
Trust	Our partner keeps promises made to our firm.	3.868	1.175	−0.726	−0.196	0.847	0.877	0.704	0.225	0.423
	Our partner is always trustworthy.	4.011	1.032	−0.880	0.178	0.911				
	Our partner has always been evenhanded in its negotiations with us.	3.867	1.154	−0.740	−0.190	0.760				

Model-fit-indices are $\chi^2(df) = 37.102(24)$, CFI = 0.988, RMSEA = 0.044, and SRMR = 0.031.
Columns show means (M), standard deviation (SD), skewness (SK), kurtosis (KT), standardized factor loadings (FL), composite reliability (CR), average variance extracted (AVE), Fornell-Larcker ratio (FLR), and Heterotrait-Monotrait ratio (HTMT).

Klimoski & Mohammed, 1994). Individuals interact and partially expose their knowledge and similarities to make differences in their knowledge visible (Hughes, Rigtering, Covin, Bouncken, & Kraus, 2018). Mutual knowledge within alliances (Zollo, Reuer, & Singh, 2002) is based on reciprocal learning (Inkpen & Tsang, 2007; Lubatkin, Florin, & Lane, 2001) and proliferates in a trustful relationship (Bouncken et al., 2020c).

From a sensemaking perspective, knowledge creation is a process of shifting or combining cognitive structures, which are representations of the world and assumptions about how it functions (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). Mutual knowledge creation stimulates creativity; hence, it is a breeding ground for innovation (Khanna, Gulati, & Nohria, 1998; Nelson & Winter, 1985). Mutual knowledge within alliances evolves stepwise through recursive processes (Bouncken et al., 2020c). In mutual knowledge creation, partners are cooperatively involved in creating knowledge by leveraging differences and creating synergies by blending their knowledge about technology, markets, management, and systems and processes in novel ways, thus allowing them to overcome established sensemaking patterns of managers (Postrel, 2002). Hence, we suggest that more innovative outcomes occur in the presence of mutual knowledge creation. However, very high levels of overlapping knowledge associated with very high levels of mutual knowledge creation will reduce the chance of finding novelties. Thus, the effect follows an inverted u-shape.

H2a: Mutual knowledge creation between partners in alliances will be positively associated with innovation value creation.

H2b: The positive influence of mutual knowledge creation on innovation value declines for high levels of this knowledge creation.

Further, mutual knowledge creation will be essential for the innovation value creation of older firms that operate in an alliance. As mentioned before, older firms will have developed more rigid organizational structures, communication routines, and sensemaking patterns. Their managers will reinforce their interpretation and sensemaking patterns so that new information or knowledge (as by the alliance partner) will not be seen as a facilitator for new thoughts but instead, be pressed or reframed into established patterns. As set out in the garbage can model long ago (Cohen, March, & Olsen, 2015; Yi, Stieglitz, & Knudsen, 2018), managers tend to just re-use old solutions and reinforce their sensemaking patterns. However, when managers in the alliance enter intense recursive interactions and knowledge transfers among each other, they might gradually change their patterns and, on this basis, develop novel innovations. Thus, when older firms achieve higher levels of mutual knowledge creation, they can activate surface and deep-level knowledge creation processes. Hence, older firms by mutual knowledge creation in the alliance realize an ‘anti-aging’ treatment towards higher levels of innovation value creation. Therefore, by mutual knowledge creation, older firms can compensate for the adverse effects on innovation set by age rigidities.

H3: Mutual knowledge creation moderates the relationship between firm age and innovation value creation in the way that the negative effect of firm age is reduced through mutual knowledge creation in the alliance.

3. Method

3.1. Sample and data collection

We used data from 296 manufacturing suppliers with major business operations in Europe to test our hypotheses, focusing on four industries in which small and medium-sized enterprise (SME) suppliers (≤500 employees) strongly contribute to innovation. Our study uses multiple data sources. First, we targeted executives who had knowledge about their firms’ long-term exchanges with buyers to retrieve information. We then sourced secondary data (e.g., firm age and number of employees) from the *Amadeus* database to combine subjective and objective measures. Of our key respondents, 34.0% were on a management board, 23.9% were in marketing, 8.0% in R&D, 5.9% in production, and 28.2% in other corporate functions. The firms in the sample were, on average, 30 years old (median: 25), had an average of 333 employees (median: 54) at the time of the survey, an average sales volume of 30.3 million euros (median: 7.0 million euros) in the preceding business year, and an average rate of return of 23.3% (median: 20.0%). The firms had operated within an alliance for an average of 85 months (median: 60 months).

3.2. Measurement model

The independent variable firm age in years was computed by the year of survey and the firm’s founding. Mutual knowledge creation (MKC) was assessed with items focusing on (1) the mutual development of something new, (2) the shared discovery of new solutions through the exchange of knowledge, and (3) the sharing and connecting of the partners’ knowledge in pursuit of project success (Clauss & Kesting, 2017). Finally, we measured innovation value creation (IVC) using items focusing on the degree to which new products (1) incorporate technology new to customers, (2) offer benefits new to customers, and (3) introduce new features to the market (Garcia & Calantone, 2002).

For each latent construct, we employ five-point, Likert-type scales ranging from “total disagree” to “total agree” or, in the case of new product superiority, “no benefit” to “very much benefit”. With a confirmatory factor analysis (CFA), we assess the model fit of the measurement

Table 2
Correlation Matrix ($n = 296$).

		Mean	(SD)	1	2	3	4	5	6	7	8	9	10
1	Firm size [a)]	4.12	1.68										
2	R&D int. [a)]	2.48	0.97	0.03									
3	Coll. duration [a)]	4.06	0.96	**0.11**	**−0.21**								
4	Trust [b)]	0.00	0.85	0.09	−0.06	−0.01							
5	OEM	0.62	0.49	0.01	0.00	0.03	−0.04						
6	Supplier	0.22	0.41	0.01	−0.08	−0.01	−0.03	**−0.34**					
7	Trade	0.10	0.30	−0.10	**−0.11**	0.02	0.03	**−0.15**	−0.09				
8	Service	0.10	0.30	−0.08	0.01	0.03	−0.05	−0.04	0.04	**0.21**			
9	Firm age	31.83	27.27	**0.45**	**−0.14**	**0.18**	0.10	0.02	−0.04	−0.05	−0.06		
10	MKC [b)]	0.00	0.97	−0.01	0.06	−0.05	**0.42**	0.05	−0.02	−0.01	0.06	−0.02	
11	IVC [b)]	0.00	0.98	−0.05	**0.18**	−0.09	**0.26**	−0.01	−0.10	0.02	−0.06	**−0.19**	**0.49**

Bold values indicate statistical significance at the 0.05 level.
[a)] For the variables whose standard deviations are greater than the mean, we transformed those variables by taking the natural logarithm. We added the value of one to the variables before taking the natural logarithm to avoid generating values with missing data after transformation (Luong, Moshirian, Nguyen, Tian, & Zhang, 2017).
[b)] For latent variables, the means are 0 by definition of the SEM assumptions.

model (Hu & Bentler, 1999, Bagozzi & Yi, 2012) and the empirical distinction of the latent variables (Rönkkö & Cho, 2020). The model fit, evaluated by a combination of root mean square error of approximation (RMSEA) <0.06, comparative fit index>0.95, and standardized root mean square residual (SRMR) <0.08, indicated the appropriate fit of the model with the empirical data (Chen, Curran, Bollen, Kirby, & Paxton, 2008, Hu & Bentler, 1999). Table 1 shows that the factor loadings of all indicators are > 0.60 (Bagozzi & Yi, 1988, Bagozzi & Yi, 2012), with composite reliability > 0.70 (Bacon, Sauer, & Young, 1995, Bagozzi & Yi, 2012), average variance extracted > 0.50, the Fornell-Larcker ratio < 1.00 (Fornell & Larcker, 1981), and HTMT < 0.85 (Henseler, Ringle, & Sarstedt, 2015).

3.3. Conditional dependence problems

All statistical analyses require conditional independence, which means that the values of the predictor variables are assigned independently of the dependent variables. Thus, a critical challenge arises because research based on data merely observes the variables in a statistical sample. When such variables are not manipulated, we do not know the origins of their variances, which implies that we do not really know whether they covary with one another with the understanding of causal inference (Ketokivi & McIntosh, 2017).

Several problems (see endogeneity bias) can occur when the explanandum may influence the explanans, or both may be jointly influenced by an unmeasured third (Antonakis, Bendahan, Jacquart, & Lalive, 2014; Esping-Andersen & Przeworski, 2015). Furthermore, a common consequence of two independent causes can render those causes dependent because information about one of the causes tends to make the other more or less likely, given that the consequence has occurred (Pearl, 2009). We included control variables to explore conditional independence and reduce the impact of potentially omitting sources in the model estimation. Because flexibility in general and a firm's capability to adapt to environmental changes depends on firm size (Hannan & Freeman, 1984), we included the logarithm of employees. We controlled for firms' R&D intensity (R&D investments per sales), as greater R&D intensity is associated with higher innovativeness. Because the process of the MKC process is associated with the familiarity of the partner, we controlled for the duration of the firm's collaboration with the partner (in months) and the inter-organizational trust (on the alliance level), using three items of Lui (2009) on a five-point Likert-type scale (see Table 1). Furthermore, the firm's position in the value chain was used as a control variable.

Many research practices are directed towards checking possible bias from Ordinary Least Squares estimator (OLS), using more robust Two-Stage Least Squares (2SLS) estimator. This method is often designed to justify existing results. However, they fail if the suitable instruments are not identified or the instruments are not exogenous. In addition to traditional research methods, mathematical algorithms and adaptive systems are increasingly used in data analysis. For example, the algorithm PC (named after its authors, Peter and Clark) (Harris & Drton, 2013; Spirtes, Glymour, & Scheines, 2000) uses conditional dependence tests (*d*-separation) for model selection in graphical modeling with acyclic directed graphs (Pearl, 2009). The result can infer information about the causal structure from observational data, which allows conclusions to be drawn about the conditional dependence of the investigated and partly unobserved sources (Kalisch, Mächler, Colombo, Maathuis, & Bühlmann, 2012). To check our theoretical model, we used this method and checked the appropriateness of this feature to discuss our results.

3.4. Parameter estimations and modeling

To test our hypotheses, we used the covariance-based structural equation modeling (SEM) approach with the software Mplus version 8.0 (Muthén & Muthén, 1998–2012). In an initial step, we included a few control variables: the firm size, R&D intensity, collaboration duration (months), trust, and then the supply chain positions: Original Equipment Manufacturer (OEM), supplier, trader, and service industry. Only R&D intensity and trust had a significant positive effect. We evaluated H1 and H2a, based on the estimated structure coefficients, if their error probability was less than 5%. We used the Latent Moderated Structural Equations (LMS) approach (Kelava et al., 2011; Klein & Moosbrugger, 2000) to model the nonlinear term of MKC in H2b and the interaction term of firm age with MKC (H3). To check for the curvilinear relationship suggested in H2b, we used the three-step procedure[1] suggested by Lind & Mehlum (2010). We expected a significant coefficient with a negative sign for the assumed inverse U-shaped relation of MKC on IVC. To decide on H3, we employed the significance of the interaction term and compared the predicted IVC for the levels of MKC in lower and higher levels of firm age.

Table 2 shows the correlations between model variables and controls. Firm age is related to larger firm size, longer collaboration duration, lesser research intensity, and lesser IVC. For mutual knowledge creation, we found significant relations of it with trust and IVC. Furthermore, IVC was also related to research intensity and trust.

[1] This procedure requires that (1) the estimated coefficients are significant and of the expected sign, (2) the slope tests on both ends of the data range are significant, and (3) the turning point is located within the data range (Haans, R. F. J., Pieters, C., & He, Z.-L. 2016. Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. ***Strategic Management Journal***, 37(7): 1177–1195).

Table 3
Results from Structural Equation Modeling (Dependent Variable is Innovation Value Creation) with MLR-estimator ($n = 296$).

	Model I				Model II				Model III				Model IV			
	Est.	S.E.	*z*-value	*p*-value	Est.	S.E.	*z*-value	*p*-value	Est.	S.E.	*z*-value	*p*-value	Est.	S.E.	*z*-value	*p*-value
Firm size	−0.028	(0.036)	−0.774	0.439	0.018	(0.040)	0.453	0.651	0.020	(0.035)	0.568	0.570	0.003	(0.036)	0.090	0.928
R&D intensity	0.193	(0.063)	3.054	0.002	0.166	(0.064)	2.579	0.010	0.131	(0.060)	2.195	0.028	0.138	(0.059)	2.332	0.020
Collaboration duration (months)	−0.047	(0.064)	−0.725	0.469	−0.027	(0.063)	−0.422	0.673	−0.039	(0.057)	−0.678	0.498	−0.039	(0.058)	−0.683	0.495
Trust	0.338	(0.084)	4.023	0.000	0.350	(0.084)	4.168	0.000	0.104	(0.082)	1.265	0.206	0.111	(0.084)	1.326	0.185
OEM	−0.032	(0.116)	−0.276	0.783	−0.031	(0.114)	−0.275	0.783	−0.104	(0.107)	−0.965	0.335	−0.112	(0.107)	−1.053	0.292
Supplier	−0.163	(0.141)	−1.159	0.246	−0.189	(0.142)	−1.331	0.183	−0.228	(0.135)	−1.689	0.091	−0.257	(0.135)	−1.902	0.057
Trade	0.078	(0.193)	0.407	0.684	0.063	(0.192)	0.330	0.742	0.046	(0.161)	0.285	0.776	0.033	(0.160)	0.207	0.836
Service	−0.163	(0.187)	−0.874	0.382	−0.173	(0.191)	−0.903	0.366	−0.312	(0.164)	−1.905	0.057	−0.355	(0.170)	−2.090	0.037
Firm age					−0.006	(0.003)	−2.185	0.029	−0.006	(0.003)	−2.209	0.027	−0.009	(0.003)	−2.642	0.008
MKC									0.500	(0.077)	6.507	0.000	0.511	(0.078)	6.587	0.000
MKC (squared)									0.116	(0.059)	1.978	0.048	0.124	(0.059)	2.118	0.034
Firm age × MKC													0.006	(0.002)	2.523	0.012
Firm age × MKC (squared)													0.004	(0.002)	2.009	0.044

Columns show unstandardized coefficients (Est.), robust standard errors (SE), *z*-values, and *p*-values.
Model-fit indices from model II: chi^2 (df) = 40.774 (32); RMSEA < 0.06 0.000; CFI > 0.95; SRMR < 0.08.

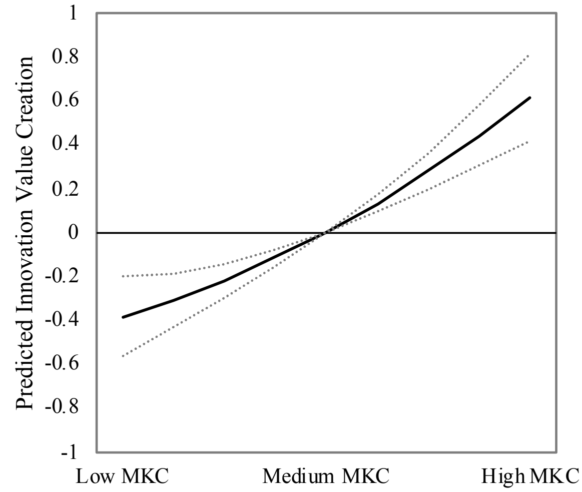

Fig. 1. Influence of mutual knowledge creation (MKC) on innovation value creation (IVC).

4. Results

Table 3 shows the results of four stepwise extended SEMs. The first model explains the 13.9% of IVC's variance by the control variables. R&D intensity and trust are relevant. By adding firm age in the second model, the explained variance of IVC increases to 17.0%. Then, by adding the linear and nonlinear terms of MKC in the third model, the explained variance of IVC increases to 37.2%. Finally, the interaction of firm age and MKC in Model IV explains 39.1% of IVC's variance.

H1 proposes that higher levels of firm age are related to decreasing IVC. We found a significant negative coefficient for firm age on IVC (γ = -0.006; z = -2.185; p = 0.029; Model II in Table 3). Thus, if firm age increased by one year, a reduction in IVC by 0.006 was predicted, and consequently, Hypothesis 1 was supported.

In the second hypothesis, we proposed that MKC promoted the IVC of the firm. Increasing MKC led to higher IVC ($\gamma = 0.500$; $z = 6.507$; $p = 0.000$; see Model III in Table 3). As such, the data revealed a positive main effect of MKC on innovation. This result was consistent with Hypothesis 2a. Additionally, a nonlinear effect ($\gamma = 0.116$; $z = 1.978$; $p = 0.048$; Model III in Table 3) is evident in the data. Specifically, as MKC increased, the impact of MKC on IVC did not approach a limit (assumed negative sign). Fig. 1 shows the results of 2a and 2b. Thus, we found a progressing slope rather than a diminishing one, as assumed in H2b.

We tested for the interaction between firm age and MKC in hypothesis H3. Fig. 2 shows the joint influence of firm age and MKC on IVC. With Hypothesis 3, we assumed that higher levels of firm age would be associated with a higher impact of MKC on IVC. Comparing the plots in Fig. 2 indicates higher levels of firm age with low MKC and a deficient level of IVC. In the presence of high MKC, the level of IVC did not differ between higher (older than 60 years) and lower levels (less than five years) of firm age. Consequently, the impact of MKC was more important for higher levels of firm age and reduced the negative effect of firm age in alliances.

This picture is distinctly determined by the significant interaction of firm age and the linear term of MKC ($\gamma = 0.006$; $z = 2.523$; $p = 0.012$; show Model IV in Table 3), and these results supported Hypothesis 3. Furthermore, firm age moderates the curvilinear relationship between MKC and innovation (H2a). We found a significant interaction between firm age and the nonlinear term of MKC ($\gamma = 0.004$; $z = 2.009$; $p = 0.044$; show Model IV in Table 3); that firm age moderated the aforementioned relationship (MKC on IVC) in a "shape-flip" fashion. With higher levels of firm age, the curvilinear influence of MKC on IVC increased, and lower levels of firm age led to a reduced curvature in the MKC-IVC relationship.

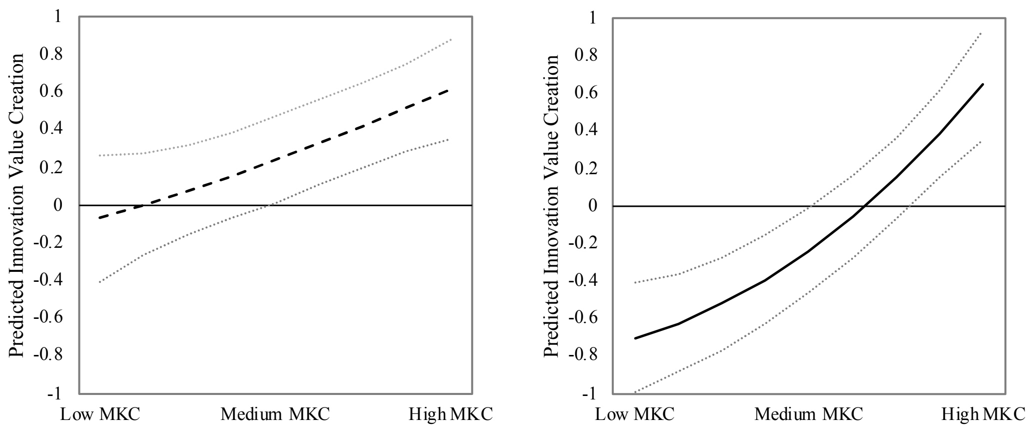

Fig. 2. The interaction of the firm age with mutual knowledge creation (MKC) on innovation value creation (IVC). The figures show the estimated IVC with increasing MKC for lower levels of firm age (left) and higher levels of firm age (right). The 'medium MKC' refers to the value representing the sample mean, subtracting one standard deviation for the notation 'low', and, respectively, for the notation 'high,' adding one standard deviation to the sample mean. The dotted lines show the confidence intervals for the estimations.

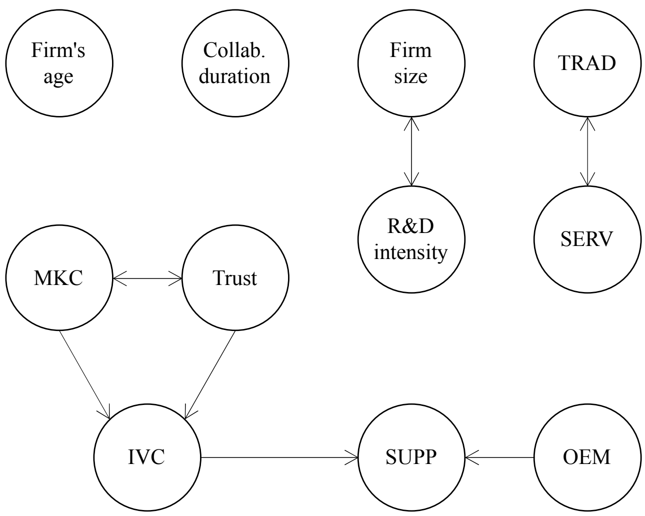

Fig. 3. The estimated causal structure of the algorithm PC in a graphical model.

As mentioned, novel algorithms might prove the independence of observations. We used all the variables from our model and checked for conditional dependence. Contrary to our assumptions, we found that firm age and IVC were (conditionally) independent (see Fig. 3).

This could mean that firms did not produce less IVC as they aged. Instead, the observed (negative) relationship could represent a conditional dependence from other sources. Our analysis showed MKC as a possible source. If firms with a higher level of age reached an equally high MKC, they were in no way inferior to young companies in terms of innovation value creation. The algorithm PC pointed out that the data identified MKC and trust as causes of IVC, with MKC and trust perhaps being recursive dependent. Finally, it can be shown that the model structures were found again and validated our theoretical and empirical analyses.

5. Discussion

Our research was interested in the effect of firm age in alliances on IVC and how this was affected by MKC among firms. Theoretically, our study combines the sensemaking perspective with the dynamic relational view to theorize about the effects of firm age and MKC in alliances on innovation (Majchrzak, Jarvenpaa, & Bagherzadeh, 2015; Seidl & Werle, 2018). Although alliances allowed for complementarities, firm age was negatively associated with IVC. We found that MKC contributed to IVC across all age levels, but most positively at the high end of the scale. MKC could compensate for the adverse effects when firms were older and thus were likely to have more rigid, less open inner and outer boundaries. Hence, we put forward that older firms can compensate for their disadvantages on innovation value, which can relate to internal rigidities and overly repeated similar sensemaking processes, when they enter MKC by allying with younger firms.

Our research results have theoretical implications. First, we show challenges for innovation for older firms despite the complementarities in alliances that the relational view suggests. Second, favorable outcomes on innovation emerge when the firms are engaged in MKC within alliances (Seidl & Werle, 2018; Wright et al., 2000). Moreover, MKC facilitates understanding of partners' strengths, weaknesses, biases, and motivations, thereby contributing directly to the sensemaking process. It allows exchanging ideas and knowledge in recursive and joint processes, thus changing rigid sensemaking patterns that otherwise would ignore avenues for novelty. The ability to clearly and accurately interpret signals is key to potentially maximizing each firm's commitment and contribution to the exchange. Fundamentally, the creation of MKC seems to compensate the negative effects from higher firm age related to higher firm age, thens we submit MKC produces an anti-aging therapy for firms towards better product innovation. Hence, we frame it as an 'anti-aging' treatment for older firms. In this, we support and specify the dynamic relational view of alliances. In a practical sense, older firms should look for suitable younger firms and employ structures that make them more agile and allow flexible and open communication with their alliance partners. The joint identification context (e.g., in a digital industry) might support the transfer of knowledge that facilitates MKC (Bouncken & Barwinski, 2021). In more open and multi-minded alliance processes, firms might find it easier to fully use their innovation potential. In addition, firms might consider new open, collaborative workspaces that allow them to work in a more inspiring and agile environment (Bouncken, Ratzmann, Barwinski, & Kraus, 2020a; Bouncken & Reuschl, 2018).

The implications should be judged in light of this study's limitations, of which two are noteworthy. First, while sensemaking is a core mechanism used to explain the effects, we can only assume the existence and relevance to our results. That is, we claim that we have directly demonstrated evidence of sensemaking through our results. Second, while all measures used in this study are published scales, the usual qualifications associated with primary data collection instruments apply here.

6. Concluding remarks

In essence, our study found that innovation increased when firms achieved high levels of MKC. In particular, older firms whose IVC was negatively affected by internal rigidities and repeated sensemaking processes could revitalize their IVC if they created mutual knowledge with younger firms in alliances. In short, firms could improve innovation even if their age increased in choosing the right juvenile partners.

Future research, building on the current results, could include alliance governance or specific (innovation) planning tools applied to the different firms to promote product success. Furthermore, some firms might be in a better position to capture value from the shared knowledge, e.g., if one firm has a higher absorptive capacity for organizational learning (Zahra & George, 2002), different from firms that might have a certain minimum level of absorptive capacity for organizational learning.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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