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Enhancing green process innovation performance: The role of regenerative unlearning and knowledge base management

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ABSTRACT

Spanish manufacturing companies are urged to adopt greener practices to mitigate their environmental footprint. However, they often lack the knowledge to do so. Following a knowledge-based approach, this study analyzes the role of strategic knowledge management in enhancing organizational green performance. It introduces the concept of regenerative unlearning, defining it as the result of an organizational change that has consequences at the organizational level. Specifically, it tests the direct influence of regenerative unlearning on green process innovation performance and its indirect influence through knowledge breadth and depth. By analyzing 310 Spanish medium-sized manufacturing companies, results show that updating and managing the knowledge base positively impacts the company's green process innovation performance. This implies that leveraging regenerative unlearning as part of companies' knowledge management strategy is part of the solution to achieving ecological efficiency in the manufacturing industry. Finally, actionable recommendations for industry leaders to improve their green performance are provided.

1. Introduction

Climate change represents one of the most pressing challenges for humanity and organizations (Robinson et al., 2022). The manufacturing industry contributes to this crisis, being the largest single emitter of Greenhouse Gas (GHG) emissions on the European continent (Eurostat, 2023). For example, the Spanish manufacturing industry is responsible for 24% of the country's total GHG emissions (INE, 2023). Therefore, the manufacturing industry has to improve its process optimization for better circularity (Urbinati et al., 2020) to support the achievement of Sustainable Development Goal 9.4, which focuses on sustainable manufacturing processes. This can be achieved by innovation in production efficiency, energy conservation, reduction of emissions and over-dependence on resource use (Serrano-García et al., 2023).

However, it has been demonstrated that green process innovation for greater circularity within manufacturing companies is impeded by a deficiency in technical skills and knowledge (Govindan et al., 2014; Salmi & Kaipia, 2022). Indeed, firms' eco-innovation and improvement of their green performance depend on their effective strategic knowledge management (KM) (Atiku, 2020). In this regard, the knowledge management literature emphasizes knowledge acquisition as a driver of innovation (Awan et al., 2021; Zhou & Li, 2012). Nevertheless, a growing body of empirical evidence suggests that merely engaging in organizational learning processes is insufficient to support companies' innovation (Cubillas-Para et al., 2023; Joo et al., 2022). Indeed, regenerating outdated or ineffective knowledge, routines, and practices to create room for new and innovative insights is also needed (Ruiz-Ortega et al., 2023). Yet, the literature has not investigated the relationship between unlearning processes and Green Process Innovation Performance (GPIP).

This study investigates this gap and argues that achieving GPIP depends on manufacturing companies' capability to regenerate and strategically manage their knowledge base. More specifically, this study proposes the new concept of "regenerative unlearning" (hereafter REU) of companies, defined as the result of a change having consequences at the organizational level (updated mental models, changed routines and relearning) (Cegarra-Navarro & Wensley, 2019; Kim & Park, 2022) in terms of knowledge base management and GPIP. Accordingly, we posit that the unlearning processes of manufacturing companies will contribute to their strategic knowledge base management and positively affect their GPIP. Based on the above, our research questions are: a) Does Regenerative Unlearning positively influence manufacturing

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companies' Green Process Innovation Performance? And b) Does the strategic knowledge base management of manufacturing companies positively influence their Green Process Innovation Performance?

To address these research questions, we analyzed the relationships between REU, knowledge breadth and depth management (knowledge base), and GPIP in a sample of 310 manufacturing medium-sized enterprises (MEs) in Spain, one of the top five of Europe's manufacturing countries (Eurostat, 2023). The analysis was carried out with SmartPLS 4.0 software. The results add to the knowledge management field by showing that improving GPIP requires the organizational ability to regenerate outdated knowledge and routines and manage their knowledge base. It further contributes to the literature by introducing the concept of Regenerative Unlearning and highlighting its criticality in the context of innovation in manufacturing MEs. Therefore, it suggests that unlearning strategies may be the key to unlocking transformative ecological efficiencies for more circularity. Finally, the study provides actionable recommendations for industry leaders seeking to overcome barriers on the path to decarbonization.

2. Theoretical framework

This study is rooted in the Resource Based View (RBV) that considers organizations as composed of a set of unique resources and capabilities (Barney, 2001) that help them to achieve competitive advantages (Estensoro et al., 2022) and superior returns (Grant, 1996). More specifically, it follows the Knowledge-Based View (KBV), where strategic knowledge management, specifically, unlearning, is considered a critical aspect of firms' innovativeness and green performance (Cooper et al., 2023). Indeed, the literature usually considers knowledge a crucial intangible asset (Müller et al., 2021) to achieve positive GPIP, as organizations may require employees to develop and update skills and knowledge (Santamaría et al., 2012).

2.1. A new approach to unlearning in the context of innovation

A growing body of empirical evidence argues that merely engaging in organizational learning processes is insufficient to support companies' innovation (Cubillas-Para et al., 2023; Joo et al., 2022). Indeed, deploying innovative processes requires members of an organization to re-evaluate and abandon existing routines and operating methods in favor of new ones (Ruiz-Ortega et al., 2023). This process is known as intentional unlearning (IU). IU occurs when an organization acknowledges that its existing knowledge base or habits are outdated or insufficient (Cegarra-Navarro et al., 2014). In the existing literature on IU, unlearning is initiated at the individual level (e.g., errors, employees' counterproductive habits …) and is overcome by "relinquishing" outdated knowledge at the individual or group level and by "relearning" at a managerial level. Therefore, the IU enablers (awareness, relinquishing and relearning) create a "feedforward flow" where individuals and managers initiate organizational change. This approach to unlearning focuses on assessing the factors that facilitate the unlearning process at both the individual and managerial levels within an organization. Consequently, IU has been measured as a formative construct.

However, academics such as Kim and Park (2022) have recently advocated for assessing visible changes and adaptations within the organization rather than focusing solely on the factors that enable the unlearning process. Consistent with this approach, Cegarra-Navarro and Wensley (2019) argue that the impact of unlearning becomes evident when there are visible outcomes. This view implies measuring unlearning from a "backward flow" perspective, acknowledging that the change has already been implemented in the organization and has consequences for all its members. In this study, the authors concur with the value of this approach and argue that investigating unlearning from a backward flow perspective may allow academics to investigate what happens at the organizational level once a change has occurred and explore what can be learned from that change. Therefore, the authors propose the concept of regenerative unlearning, defined as a reflective construct that manifests through observable outcomes. The term "regenerative" has been chosen as it represents a transformative process based on pre-existing knowledge and established routines. It encapsulates the idea of revitalizing a deteriorated or obsolete entity by discarding harmful habits or behaviors (Makkonen et al., 2014). Building upon the Cegarra-Navarro and Wensley and Makkonen et al. (2014) studies, we propose to measure REU through its three main organizational outcomes: (i) updated mental models, (ii) altered routines, and (iii) organizational relearning.

Fig. 1 captures the key differences between the current IU approach and the REU approach proposed in this study. The "backward flow" approach focuses on organizational outcomes rather than individual factors. Thus, it expands the theoretical relevance and practical applicability of unlearning as a trigger for regeneration, renewal, and competitiveness within firms pursuing green innovations. It has particular relevance in medium-sized companies, where, unlike in small companies, all the organizational members do not participate in the change processes, when many changes are imposed. The hypotheses developed in the next section aim to investigate the influence of REU processes of medium-sized manufacturing companies on their strategic knowledge base management and GPIP. More specifically, they test whether regenerative unlearning promotes greater breadth and depth of knowledge, contributing positively to their GPIP.

2.2. Hypothesis development

Green Process Innovation (GPI) is one of the tools available to manufacturing companies to reduce their environmental footprint. It refers to changes or improvements made to the production or service operations of a business (Nwankpa et al., 2022) aimed at reducing cost, waste, pollution, or energy consumption (Achi et al., 2022; Khan et al., 2021; Liao et al., 2023; Zameer et al., 2021). The effectiveness of GPI can be evaluated by assessing a company's environmental performance,

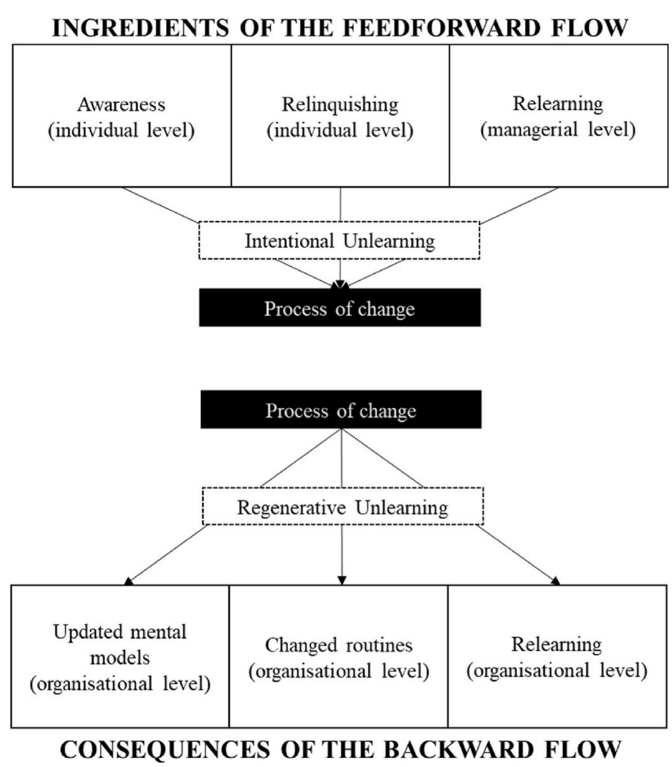

Fig. 1. Illustration of the difference between the enablers of IU (feedforward flow) and the outcomes of REU (backward flow).
Source: own elaboration

referred to as Green Process Innovation Performance (GPIP). In the innovation field, studies have shown that a company's ability to innovate relies on the strategic management of its knowledge base, composed of Knowledge Breadth (KB) and Depth (KD) (Zhang et al., 2023a; Zhou & Li, 2012).

KB and KD are different yet complementary concepts. Knowledge Breadth refers to the company's wide range of know-how applicable in different contexts (Wu & Shanley, 2009; Zhou & Li, 2012). In the context of this study, we approach it as the holistic understanding of the importance of improving environmental performance within an organization. Knowledge Depth refers to the degree of expertise of a company in a particular knowledge area (Wu & Shanley, 2009), such as their specialization in GPI. In Spanish manufacturing MEs, companies willing to implement environmentally responsible improvements to their operations need a dual and strategic focus on KB and KD (Govindan et al., 2014). For example, a company implementing solar panel technology within its processes will need a broad understanding of solar energy and photovoltaic technologies, regulations, and financing options (KB) and a specific understanding of safety protocols, expertise in electrical engineering and the ability to assess the project's viability (KD).

However, exploiting a company's accumulated knowledge base can only be beneficial if obsolete or counterproductive knowledge is continually screened out, relinquished, or modified (Cubillas-Para et al., 2023). Therefore, REU can generate competitive advantages for firms by allowing them to modify and redeploy their knowledge structures (Khin Khin Oo & Rakthin, 2022). More specifically, REU encourages organizational members to think outside the box and incorporate sustainable practices, thus broadening the company's knowledge range (KB).

Additionally, REU comes into play when an organization identifies a discrepancy between its goals and current resources, prompting the development of new expertise and skills essential for achieving the desired outcomes (KD) (Cegarra-Navarro & Wensley, 2019). For instance, a manufacturing company might consider the environmental impact of the life cycle of their products by redesigning them to include eco-friendly materials and introducing green processes. By doing so, the company expands its knowledge in different areas such as materials choices, new practices, new suppliers, circular economy models or regulation (KB), and expertise, green skills, and specific regulation (KD) needed to achieve a sustainable design. Following this rationale, we propose the following hypotheses:

Hypothesis 1. REU has a positive direct effect on KB of medium-sized manufacturing firms.

Hypothesis 2. REU has a positive direct effect on KD of medium-sized manufacturing firms.

In dynamic environments characterized by rapid changes, such as those driven by climate change, the performance of organizations depends on their continuous ability to adapt the configuration of resources to respond to shifts in the market (Eisenhardt & Santos, 2006). Therefore, to reduce the environmental footprint of their processes, manufacturing companies are required to challenge their status quo (Van Oers et al., 2023), changing outdated mental patterns, beliefs, practices, and processes (Feola et al., 2021; Hazas & Nathan, 2017). This can be achieved with an organizational "good shake," generating a new lens to examine existing knowledge (Zhou & Li, 2012), thereby mitigating the risk of cognitive inertia. Thus, fostering GPI among manufacturers requires several strategic initiatives, such as the introduction of new organizational practices (Bataineh et al., 2023), nurturing learning curves, critically assessing routines (Abdullah et al., 2016), discarding the obsolete ones, assimilating new knowledge, and relinquishing the outdated one (Cegarra-Navarro et al., 2014).

Based on the above, this study argues that REU can allow companies to overcome cognitive inertia and support their innovation efforts by updating and redeploying their knowledge base, routines, and processes. Consequently, we propose that the REU of medium-sized manufacturing enterprises will improve their GPIP.

Hypothesis 3. REU has a positive effect on GPIP.

The literature has shown that a wide range of organizational knowledge (KB) supports the search, absorption, and utilization of knowledge for innovation (Wu & Shanley, 2009; Zhang et al., 2023a). This means that KB can enable an organization to identify new strategic areas needing in-depth expertise for further development (Martínez-Ros & Kunapatarawong, 2019). In addition, when organizations face changes and disruptive situations, the orchestration and coordination of broad knowledge in different technical areas can lead to a deeper understanding of complex problems. Despite the gap in the literature addressing and investigating the impact of KB on organizations' KD, real-case scenarios can provide empirical foundations for this relation. For example, NASA exemplified how a thousand experts and stakeholders' knowledge breadth was coordinated to achieve the first landing on the moon (Martínez-León et al., 2012). The production of smart prosthetics is another example of coordination in the manufacturing industry, with a wide range of knowledge in engineering, medicine, materials, regulation, and bioethics. Without the combination of this KB, these companies would not have built the necessary expertise to meet the market needs. Based on the above, we argue that organizational KB will positively influence KD.

Hypothesis 4. Organizational KB has a positive direct effect on its KD.

Research has also shown the influence of organizational knowledge on innovation outcomes (Leal-Rodríguez et al., 2013), innovation performance (Ferraris et al., 2017), green supply chain management (Govindan et al., 2014) and green innovation performance (Albort-Morant et al., 2018). In this vein, Xie et al. (2022) have highlighted the detrimental impact of the lack of knowledge and technical expertise on GPIP. In addition, Carlo and Rose, 2012 showed that an organization that increases its knowledge depth will develop its expertise and propensity to seek process innovation. Indeed, if organizations do not have expertise and knowledge on green innovation, they will not embrace green innovation initiatives such as GPI (Abdullah et al., 2016). Recent research by Zhang et al. (2023a) reinforces these findings, demonstrating the positive influence of knowledge depth on process innovation. Accordingly, we posit that a strategic focus on enhancing the knowledge depth of medium-sized manufacturing companies will positively impact their GPIP. Therefore, we suggest the following hypothesis:

Hypothesis 5. KD has a positive impact on GPIP.

Testing these hypotheses can provide a theoretical understanding of how the backward flow of regenerative unlearning can directly translate into improved green innovation outcomes within manufacturing companies and indirectly through the strategic management of their knowledge base. Fig. 2 shows a summary of the hypotheses proposed in this section.

3. Methodology

3.1. Data collection

This study focused exclusively on medium-sized Spanish manufacturing companies, acknowledging the unique characteristics that set these firms apart from both large and small companies in the context of innovation. Knowledge management and innovation studies have grouped small and medium enterprises in their sample (Cegarra-Navarro et al., 2016; Pett et al., 2024; Piwowar-Sulej et al., 2024). However, this study considers that MEs, compared to small ones, are more resourceful and proactive in environmental management systems thanks to their better access to economies of scale, sources of funding and investing capacity (Díaz-Chao et al., 2016). Smaller enterprises often face limitations in terms of financial resources, skills, and

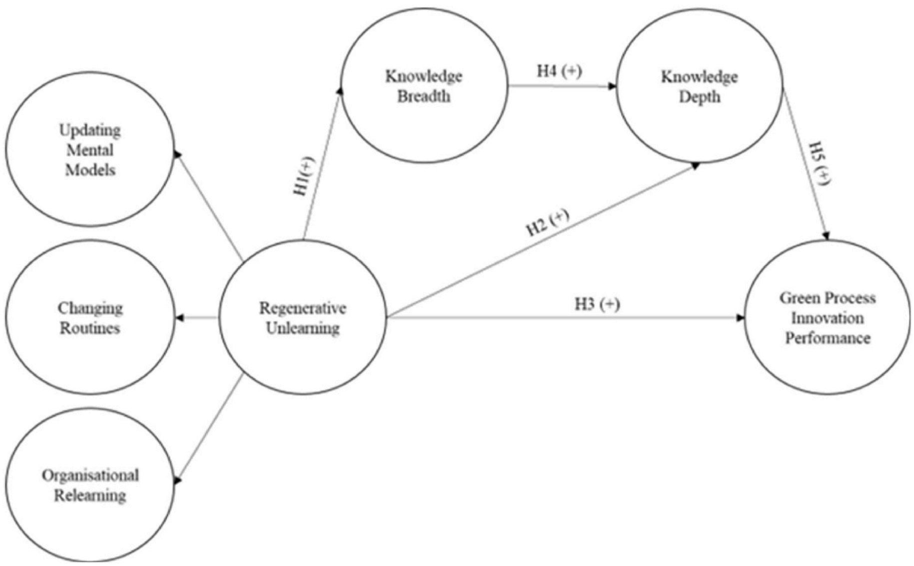

Fig. 2. Proposed model.
Source: own elaboration

capabilities (Wong et al., 2020). Therefore, we argue that both companies should not be analyzed under the same group.

In addition, Spanish companies were chosen as Spain is one of the top 5 European countries contributing to the manufacturing economy (World Population Review, 2023). In fact, the study of Montoriol-Garriga and Díaz (2021) showed the need for Spanish manufacturing companies to evolve towards more sustainable industrial models. The sample comprises companies with at least five years of activity based on the rationale that when organizations gain years of experience, they may face resistance to change, leading to structural inertia (Sirén et al., 2017) stemming from well-established routines. Considering that green innovation directly impacts these routines (Cegarra-Navarro & Wensley, 2019), it was crucial for the relevance of this study to consider organizations that had the chance to establish and consolidate their routines. Furthermore, more experienced organizations tend to show more background and resources to develop environmental innovations (Tang et al., 2018).

The data were collected via a structured questionnaire. A pilot study was conducted involving professors from two universities and managers from 10 companies to validate the questionnaire design. Following the pilot study and subsequent review stages, the final questionnaire was distributed to managers in the companies of the sample. The data collection period spanned from early June to July 2021. The population sample comprised managers of manufacturing MEs included in the SABI database (https://sabi.bvdinfo.com) with more than five years of experience in the manufacturing sector, totalling 3465 companies. From this population, a sample of 1686 companies was randomly selected, resulting in the participation of 310 experts. The response rate of 18.38%, with a factor of error of 5.76% for p = q = 50% and a level of reliability of 95.5%, is greater than the required 15% suggested by Menon et al. (1996) for surveys involving senior management. Table 1 indicates the respondents' demographic.

Before collecting data, the f^2 size parameter or minimum sample size was estimated. The f^2 size parameter represents the change in the value of R^2 when an exogenous variable is omitted from the model. Cohen (1977, 2013) justifies three levels of f^2 sizes (i.e., small 0.02; medium 0.15; and large 0.35), often requiring a medium effect of 0.15. It should be noted that the f^2 size refers to the underlying population rather than a specific sample. To calculate it, we used G*Power 3.1 (Cunningham & McCrum-Gardner, 2007), relying on an a priori test with a Linear Multiple Regression setting. Results of the analysis show that for an f^2 size effect of 0.15, a sample of 89 questionnaires is required. In our case, we observed a f^2 above 0.15 for the three dependent variables (GPIP = 0.28, KB = 0.68, KD = 0.21 and GPIP = 0.28, respectively), indicating a measure of practical significance in the magnitude of the effects. We have also used the inverted square root analysis proposed by Kock and Hadaya (2018) to reinforce these results. Assuming a significance level of 0.05 and a minimum patch coefficient of 0.164 for the relationship between "*KD" and "GPIP"* (see Table 2), the minimum sample size is 230 (Kock & Hadaya, 2018). Therefore, the reliability of the statistical analysis and the inverse square root method ensures that our sample is greater than the minimum required.

Potential non-response bias was addressed by comparing the 155 early and 155 late responses regarding REU and GPIP. The independent sample *t*-test revealed no significant difference between the two groups ($p = 0.543$ and $p = 0.385$, respectively). To prevent common method variance bias, we used several methods. First, we applied a post hoc

Table 1
The respondents' demographic.

Gender	Male	Frequency = 228	73.5%
	Female	Frequency = 82	26.8%
Age	Min = 24	Max = 76	Average = 45.36
Company size	Min = 50	Max = 249	Average = 127.51
Area	Marketing & Sales	Frequency = 14	4.5%
	Production	Frequency = 114	36.8%
	Human Resources	Frequency = 13	4.2%
	Research & Development	Frequency = 76	24.5%
	Accounting & Finance	Frequency = 7	2.3%
	Supply Chain Management	Frequency = 18	5.8%
	Other	Frequency = 68	21.9%

Table 2
Statistical remedy of common method variance (CMV).

	Without including blue intention	Including blue intention
REU→KB	$0.637(R^2 = 0.406)$	$0.635(R^2 = 0.407)$
REU→KD	$0.235(R^2 = 0.225)$	$0.245(R^2 = 0.235)$
REU→GPIP	$0.371(R^2 = 0.215)$	$0.359(R^2 = 0.229)$
KB→KD	$0.289(R^2 = 0.225)$	$0.286(R^2 = 0.235)$
KD → GPIP	$0.164(R^2 = 0.215)$	$0.168(R^2 = 0.229)$

common method variance (CMV) assessment with Harman's single factor using exploratory factor analysis (EFA); one factor explained 38.71% of the variance, which is well below the threshold of 50% (Podsakoff et al., 2012). Second, the measured latent marker variable (MLMV) approach was used to detect potential problems of CMV, a method suggested for handling CMV in PLS-SEM models (Chin et al., 2013). Following the MLMV approach, a variable measuring responder's blue intention with four items was included (Miller & Simmering, 2022), since it is measured at the respondent's personal level and does not belong to the same domain as the variables included in the proposed model. Table 2 shows that the difference found in the R^2 value of endogenous variables after taking out the responder's blue intention is not significantly different since, in all cases, it is less than 10% (Chin et al., 2013; Podsakoff et al., 2003). These additional tests reinforce that the model proposed is free of CMV issues.

3.2. Variables measurement

Variables were measured on a 7-point Likert scale using previously validated scales in literature. Nine items adapted from Cegarra-Navarro and Wensley (2019) and Makkonen et al. (2014) were used to measure REU. These items reflect the outcomes of unlearning: update of mental models, change of routines and relearning. KB and KD were measured by adapting the scale proposed by Zhou and Li (2012). Specifically, three items measured KB as the level of engagement in R&D activities, and four items assessed the depth of the company's knowledge regarding its specific industry. Finally, GPIP was measured based on four items adapted from Chen et al. (2006) referring to the green manufacturing processes in which the company has been involved in the last three years. Among these indicators, the reduction of hazardous substances (Chen et al., 2006) and raw materials such as water, electricity, coal, or oil (Kawai et al., 2018) were included (see Appendix 1).

Furthermore, we have included the gender and age of the managers as two control variables to explore their potential effects on the proposed relationships. Prior studies have underscored that the age of an executive significantly influences their approaches to information management practices and environmental knowledge (Ma et al., 2019). Additionally, research indicates that an individual's age shapes their attitudes toward social and environmental responsibility (Wiernik et al., 2013) and influences their environmental attitudes and beliefs (Milfont et al., 2021). Finally, empirical evidence also revealed the impact of the manager's and CEO's gender on the ecological innovation practices adopted by businesses (Javed et al., 2023; Lin et al., 2022).

3.3. Assessment of the measures

Latent variables were measured with the items shown in Table 3, after adjusting them as a result of the Confirmatory Composite Analysis (CCA) and the MICOM analysis. Standardized loadings and all measures of composite reliability were larger than 0.7 and 0.8, respectively. Average Variance Extracted (AVE) values surpass the threshold parameter of 0.5 for convergent validity, and the threshold value of Cronbach's alpha exceeds 0.8 (Henseler et al., 2014). Following Hair et al. (2017), there is no multicollinearity problem as all the generated Variance Inflation Factors (VIFs) are below the threshold value of 5, ranging from 1.436 to 3.863.

Fornell-Larcker and Heterotrait-Monotrait criteria were used to test the discriminant validity for each construct (see Table 4). According to this criterion, the AVE value has to be higher than the correlation coefficient between the competent and all the distinct variables for each latent variable. In this study, the threshold value of the HTMT is below 1 for all constructs, showing the discriminant validity of the constructs (Henseler et al., 2014).

Following the two-stage approach proposed by Sarstedt et al. (2019), REU was operationalized as a second-order predictor, independent, and reflective-reflective construct. In the first stage, we got the score of changed routines, updated mental models, and relearning constructs without including the second-order construct in the model. In the second stage, regenerative unlearning was measured with the first-stage scores.

4. Results

4.1. Measurement model

We assessed the significance of the path model relationships using bootstrapping analysis with 5000 subsamples (bias-corrected and accelerated bootstrap, two-tailed test) in measurement and structural models (Hair et al., 2011). As shown in Table 5, the loadings are statistically significant. Furthermore, the VIF values indicate the absence of collinearity. As a measure of CCA considering the casual nature of

Table 3
Model estimates (first-order constructs).

		VIF	Weight	*t*-value	Loading	*t*-value	
UpMM	$UpMM_1$	1.768	0.369	25.172	0.841	38.698	AVE = 0.734
	$UpMM_2$	1.768	0.376	26.838	0.843	34.058	SCR = 0.892
	$UpMM_3$	2.594	0.421	26.495	0.885	51.887	α = 0.819
ChR	ChR_1	3.379	0.354	51.472	0.923	95.367	AVE = 0.858
	ChR_2	3.532	0.366	56.707	0.934	84.477	SCR = 0.948
	ChR_3	3.103	0.360	57.534	0.922	78.104	α = 0.917
REL	REL_1	2.918	0.344	54.841	0.910	64.521	AVE = 0.856
	REL_2	3.863	0.366	48.158	0.941	115.86	SCR = 0.947
	REL_3	3.200	0.371	52.313	0.924	91.433	α = 0.916
KB	KB_1	1.598	0.318	15.661	0.791	25.229	AVE = 0.767
	KB_3	2.859	0.401	24.838	0.916	80.028	SCR = 0.908
	KB_4	2.771	0.416	25.149	0.914	90.487	α = 0.847
KD	KD_1	2.678	0.236	7.519	0.812	24.199	AVE = 0.623
	KD_3	2.423	0.277	8.396	0.783	20.811	SCR = 0.869
	KD_4	1.436	0.304	8.522	0.734	17.074	α = 0.806
	KD_7	1.455	0.446	8.665	0.826	31.11	
GPIP	$GPIP_1$	2.348	0.276	13.713	0.862	45.939	AVE = 0.682
	$GPIP_3$	1.796	0.323	12.562	0.814	27.897	SCR = 0.895
	$GPIP_4$	2.037	0.314	12.877	0.845	35.112	α = 0.844
	$GPIP_7$	1.626	0.301	11.577	0.780	25.322	

Notes.Updating mental models→ UpMM; Changing routines→ ChR; Relearn→REL; Knowledge Breadth→KB; Knowledge Depth→KD; Green Process Innovation Performance→GPIP; Variance inflation factor→ (VIF); Average variance extracted→ (AVE); Scale Composite Reliability→ (SCR); Cronbach's alpha→ (α).

Table 4
Discriminant validity analyses.

	Mean	S.D	HTMT	Fornell-Larcker					
				UpMM	ChR	REL	KB	KD	GPIP
UpMM	4.873	1.213	**0.736**	***0.857***					
ChR	4.608	1.410	0.736	0.639	***0.926***				
REL	5.343	1.236	0.696	0.603	0.639	***0.925***			
KB	5.224	1.328	0.651	0.532	0.579	0.495	***0.876***		
KD	6.322	0.599	0.423	0.308	0.313	0.328	0.790	***0.790***	
GPIP	5.159	1.280	0.461	0.362	0.371	0.409	0.378	0.313	***0.826***

Notes.Standard Deviation→(S.D); Heterotrait-monotrait ratio of correlations→(HTMT); Update mental models→ (UpMM); Change routines→ (ChR); Relearn→(REL); Knowledge Breadth→(KB); Knowledge Depth→(KD); Green Process Innovation Performance → (GPIP); Diagonal values (square root of AVE are in bold) should be higher than off-diagonal correlations shown below the diagonal line.

Table 5
Model estimates (second-order constructs).

Constructs		VIF	Loadings	Confidence Intervals		
				2.5%	97.5%	
Regenerative Unlearning	UpMM	1.897	0.859	0.814	0.894	AVE = 0.751
	ChR	2.037	0.881	0.849	0.907	SCR = 0.901
	REL	1.895	0.860	0.812	0.898	HTMT = 0.726
Knowledge Breadth	KB_1	1.598	0.791	0.721	0.844	AVE = 0.767
	KB_3	2.859	0.916	0.892	0.936	SCR = 0.908
	KB_4	2.771	0.791	0.892	0.932	HTMT = 0.726
Knowledge Depth	KD_1	2.678	0.812	0.736	0.865	AVE = 0.623
	KD_3	2.423	0.783	0.693	0.844	SCR = 0.869
	KD_4	1.436	0.735	0.634	0.804	HTMT = 0.423
	KD_7	1.455	0.826	0.772	0.874	
Green Process Innovation	$GPIP_1$	2.348	0.862	0.821	0.895	AVE = 0.682
	$GPIP_3$	1.796	0.813	0.748	0.864	SCR = 0.895
	$GPIP_4$	2.037	0.846	0.792	0.887	HTMT = 0.521
	$GPIP_7$	1.626	0.780	0.712	0.834	

	Estimated Model	Hi95	Hi99	Saturated Model	Hi95	Hi99
SRMR	0.044	0.043	**0.047**	0.044	0.041	**0.044**
d_{ULS}	0.233	0.219	**0.264**	0.227	0.179	**0.237**
d_G	0.123	0.108	**0.128**	0.122	0.108	**0.127**

Notes.The bold figures indicate the compliance level with the adjustment index. SRMR: Standardized Root Mean Square Residual, d_{ULS}: Unweighted Least Squares Discrepancy, d_G: Geodesic Discrepancy; Variance inflation factor→(VIF); Average variance extracted→ (AVE); Scale Composite Reliability→ (SCR); Heterotrait-monotrait ratio of correlations→(HTMT).

PLS-SEM analysis (Cegarra-Navarro et al., 2020), the fit indices for the saturated model from our proposed model were calculated (Benitez et al., 2020). We confirm the proposed measurement model as all fit indices for the saturated model meet the requirements. The fit statistics for the structural model show a reasonable data fit. The standardized root mean square residual (SRMR) value of the measurement model was 0.044, and all discrepancies were below the 99% quantile of the bootstrap discrepancies (Hi_{99}), which suggests a good measurement model fit (Benitez et al., 2020).

4.2. Structural model

First, we checked whether the independent variable (REU), potentially being a source of endogeneity on dependent variables (i.e., KB, KD, and GPIP), is distributed non-normal (Hult et al., 2018). We did this by running the Cramer-van Mises test on the standardized composite scores of REU, which provides the estimation of the PLS-SEM model (Becker et al., 2022). If the *p*-value is less than 0.05, the variable does not follow a normal distribution. As the results indicate a $p = 0.000$, the independent construct has non-normal distributed scores, which allows us to analyze the endogeneity with Gaussian copula analysis. Second, we ran the Gaussian copula analysis, adding a copula for each independent variable of each dependent variable. There is one independent variable (i.e., REU) and there are three dependent variables (i.e., KB, KD, GPIP); therefore, we added five Gaussian copulas. None of the five copulas introduced in our model was significant. Therefore, endogeneity is not an issue when estimating the relationships in our proposed model, mainly for the final dependent variable: GPIP.

By using bootstrapping (5000 resamples), we examined the model estimates from the second stage to test the hypotheses. As shown in Table 6, the positive relationship between REU and KB ($a1 = 0.618$, $p < 0.01$), KD ($a2 = 0.216$, $p < 0.01$) and GPIP ($a3 = 0.372$, $p < 0.01$) supports hypotheses H1, H2 and H3, respectively. Furthermore, the findings reveal a direct relationship between KB and KD ($a4 = 0.244$, $p < 0.01$), supporting H4. Finally, H5 is supported as the results confirm the direct relationship between KD and GPIP ($a5 = 0.179$, $p < 0.01$). Managers' age and gender were not found to be significant (see Table 6). These findings align with studies carried out in the field of knowledge

Table 6
Structural model.

Hypotheses	Path coefficient	Confidence Intervals		(p-value)	f-square	R^2
		2.5%	97.5%			
H1: REU→KB	$a_1 = 0.618$	0.537	0.694	0.000	0.618	0.382
H2: REU→KD	$a_2 = 0.216$	0.088	0.350	0.002	0.035	0.171
H3: REU→GPIP	$a_3 = 0.372$	0.261	0.483	0.002	0.153	0.221
H4: KB→KD	$a_4 = 0.244$	0.110	0.380	0.002	0.045	0.171
H5: KD → GPIP	$a_5 = 0.179$	0.068	0.297	0.000	0.036	0.221
Gender→ GPIP	$a_5 = 0.035$	−0.06	0.128	0.479	0.002	0.221
Size→ GPIP	$a_5 = -0.018$	−0.12	0.079	0.717	0.000	0.221
Indirect effect		2.5%	97.5%	(p-value)	R^2	
REU→KB→KD	$a_1xa_2 = 0.151$	0.067	0.240	0.001	0.171	
REU→KB→KD→GPIP	$a_1xa_2xa_5 = 0.066$	0.024	0.115	0.005	0.221	
KB→KD→GPIP	$a_4xa_5 = 0.044$	0.011	0.093	0.037	0.221	

Notes.Regenerative Unlearning→(REU); Knowledge Breadth →(KB); Knowledge Depth →(KD); Green Process Innovation Performance →(GPIP).

management that have not found significant gender-based knowledge-sharing differences (Tohidinia & Mosakhani, 2010; Xue et al., 2011). Also, the results support the study of Cegarra-Navarro et al. (2011), which found that the manager's age had no significant influence on the unlearning context.

Then, we evaluated the predictive capacity of the structural model with the cross-validated redundancy index (Q^2) (Chin, 1998). Q^2 was estimated using the blindfolding procedure, indicating a satisfactory predictive power of the structural model as it was greater than zero ($Q^2_{GPIP} = 0.14$; $Q^2_{KD} = 0.093$; and $Q^2_{KB} = 0.268$). These results support hypotheses H1, H2, H3, H4, and H5. We also tested the indirect effects by conducting a post hoc indirect effect analysis (Preacher & Hayes, 2008). As the intervals of the bootstrapping analysis do not contain the zero value, we can conclude that (1) KB mediates the relationship between REU and KD, (2) KB and KD mediate the relationship between REU and GPIP, and (3) KD mediates the relationship between KB and GPIP. These mediating effects imply that KB regeneration helps to regenerate KD and enhance GPIP. A possible explanation is that when the organization actively updates its range of knowledge fields, it further improves its expertise and understanding of a specific topic within a broader domain, enhancing employee cooperation. This, in turn, can lead to improved problem solving and innovation (Zhang et al., 2023b). In other words, as the organization regenerates its knowledge, employees' skills, and insights, it improves the environmental performance of its processes (Malik et al., 2023).

5. Discussion

This study aims to analyze whether REU and strategic knowledge base management positively influence Spanish medium-sized manufacturing companies' Green Process Innovation Performance. The quantitative analysis of the data collected via a survey shows the validity of the five hypotheses proposed based on our literature review. First, REU exerts a direct positive effect on knowledge breadth (H1), depth (H2), and GPIP (H3). Second, KB of an organization has a positive direct effect on its knowledge depth (H4), which in turn positively impacts GPIP (H5). Therefore, the findings answer the study research questions by demonstrating that both REU and the effective management of KB and KD positively contribute to GPIP. Several theoretical contributions and practical implications are derived from these results, which are developed below.

First, this study contrasts with the current literature by adopting a reflective and organizational perspective on unlearning. This new approach addresses the calls from Kim and Park (2022) and Cegarra-Navarro and Wensley (2019) to shift the research focus towards exploring the consequences of a process of change (regenerative unlearning) rather than its enablers (intentional unlearning). Indeed, the measurement of REU is derived from assessing its organizational outcomes (updated mental models, changed routines, and new competencies and skills relearned). Furthermore, previous studies primarily examined employees and managerial levels (i.e., feedforward flow). In contrast, this study analyzes its backward flow by acknowledging that the organization can be the source of individual and managerial change. It also adds to the current body of knowledge by carrying out the first empirical attempt to measure unlearning as a reflective concept. In doing so, this study demonstrates the value of investigating unlearning from a backward flow perspective. It paves the way for academics to investigate further what happens at the organizational level once a change has occurred and refine and expand the proposed concept of REU in different organizational contexts.

Second, this study contributes to the growing body of literature on organizational unlearning by examining the role of REU in the context of green process innovation and environmental sustainability. The results reveal that REU has a significant positive impact on GPIP. Therefore, the update of mental models, change of routines and relearning processes allow Spanish manufacturing companies to achieve a better GPIP, mitigate their environmental footprint and meet their stakeholders' needs (Acquah et al., 2021). These results align with Cousins et al.'s (2019) study, arguing that trade organizations need experts with updated skills to implement environmental initiatives effectively. Moreover, they align with the literature showing that the inability to adapt and update knowledge can hinder organizations' innovation capacity (Gohoungodji et al., 2020). As a result, REU can be regarded as a critical response mechanism that results from changes, such as the need for more circularity in the supply chain models (Hvid Jensen, 2024). Hence, this research contributes to the advancement of the unlearning theory and sheds light on the potential of micro-level REU processes to act as enablers of the macro-level supply chain transition towards circularity and sustainability, driven by the evolving dynamics within the supply chain ecosystem. These results can be particularly relevant to MEs, which are likely to have a complex supply chain that can benefit from the transformations towards environmental objectives. Also, midsize companies can be faster than small companies at "sensing" change in their ecosystem and adapting to it than larger companies (Sher, 2021).

Finally, this study contributes to KBV confirming the pivotal role of a firm's knowledge base as a source of sustainable competitive advantage. It demonstrates that active management and updating of their knowledge base (KB and KD) allow Spanish manufacturers to adapt their organizations toward better process efficiency and lesser environmental footprint. More specifically, the results show that a better GPIP can be achieved when REU is strategically leveraged to develop the firms' KB, which will act as a scaffold and groundwork for subsequent deepening of understanding in specific areas and specialized learning (KD). That can be explained by manufacturing companies operating in rapidly evolving business landscapes, where challenges such as climate change and stakeholder demand for sustainability are continuously shifting (Salmi & Kaipia, 2022). Therefore, broadening their knowledge base across diverse domains enhances their ability to adapt to these dynamic conditions and identify emerging opportunities related to sustainable processes. Once the companies have recognized GPI as an opportunity, they can strategically deepen their Knowledge (KD) in specific areas that align with their core competencies or emerging market trends. These results align with the conclusions of authors such as Wu and Shanley (2009) and Zhang et al. (2023b), who argued that a broad knowledge base helps companies to facilitate the absorption and utilization of deeper knowledge. They also align with the study by Shehzad et al. (2023), which confirms the important role of knowledge in developing GPI. In summary, the results bring together the sustainability and knowledge management literature by demonstrating the strategic role of managing and updating knowledge breadth and depth in driving green performance.

6. Managerial implications

Based on the above, several recommendations can be drawn for manufacturing industry managers seeking to support the achievement of Sustainable Development Goal 9.4 towards a more sustainable production model.

The backward flow perspective of unlearning highlights the value of analyzing what happens after a change has occurred within an organization (Kim & Park, 2022). Therefore, when implementing or imposing organizational change, managers must go beyond merely introducing the change itself. They must actively facilitate and monitor the REU process to ensure its successful integration and sustained impact at the organization level. Managers should create an environment that encourages and supports REU, enabling employees to challenge existing assumptions, question established procedures, and embrace new ways of thinking and operating.

As the results show that REU directly impacts GPIP, managers should prompt critical evaluation of their firm's knowledge stocks and flows by undertaking initiatives that challenge existing mental models, routines, and competencies. In doing so, managers should prevent the core capabilities of the company from becoming rigid or outdated and create space for the generation of new ideas that keep the organization adaptive. Training and development efforts to enable idea sharing, collaboration, and innovative thinking across all workers can positively impact GPIP. Managers aiming to drive sustainability via greener processes should thus adopt a holistic strategic knowledge management and development strategy—building specialist skills alongside company-wide cognitive skills. These findings support the views of Chughtai and Khan (2023), who stressed that knowledge sharing and work engagement significantly mediate the link between knowledge-oriented leadership and employees' innovative performance.

The findings show that regenerating KB can support the update of KD, leading to better green performance. From a managerial perspective, understanding the sequential relationship between KB and KD to improve GPIP offers valuable insights. Managers can leverage this finding to inform decision-making related to resource allocation, employee development, and knowledge management, ensuring a strategic balanced approach for both KB and KD. These findings are particularly relevant to managers of MEs as they typically have more resources that can be allocated for GPI compared to their smaller counterparts, and their agility allows for more effective deployment than that of larger firms (Hofstede Insights, 2022).

Managers aiming to drive sustainability via greener processes should thus adopt a holistic knowledge management and development strategy. In addition, the findings suggest that managers supporting the continuous process of cognitive updating among employees participate in developing the collective expertise of the entire organization (i.e., REU→KB→KD). Also, when REU occurs, the regenerated KD can be leveraged by companies to innovate and improve their GPIP. Thus, companies should not underestimate their intangible resources when adopting organizational changes. For that purpose, REU may help maintain enough employees with the advanced knowledge required to implement more efficient process innovations, reduce their environmental impact, and sustain financial performance. Therefore, managers can prompt critical evaluation of their firm's knowledge stocks and flows by undertaking initiatives that challenge existing mental models, routines, and competencies. In doing so, they can prevent the company's core capabilities from becoming rigid or outdated and create space for generating new ideas that keep the organization adaptive.

7. Conclusion

In today's dynamic business landscape, companies must continually evolve to remain competitive and meet changing market demands, particularly in the context posed by climate change. In this context, this study has demonstrated the role of REU in improving the green performance of manufacturing companies. In addition, the study proposes the new concept of REU, which refers to the unlearning process that an organization can undergo due to changes in its environment. More specifically, it investigates the impact of REU on knowledge base management and its direct and indirect positive effects on GPIP. To do so, a quantitative analysis of a survey of 310 managers of Spanish manufacturing medium enterprises was carried out using SmartPLS software.

The findings show that REU plays a crucial role in facilitating the transition of Spanish manufacturing MEs towards sustainability. It also suggests that following the evolving dynamics within the supply chain ecosystem, firm-level REU could serve as enablers of the transition towards improved circularity and greener practices. In addition, this study confirms the crucial role of a firm's knowledge base as a source of sustainable competitive advantage, as proposed by the KBV. It demonstrates that active management and updating of their knowledge base (KB and KD) allow Spanish manufacturers to adapt their organizations toward better process efficiency and lesser environmental footprint.

Despite all the hypotheses being fulfilled, this study presents some limitations that pave the way for future lines of research. First, this study is the first attempt to measure unlearning through its consequences from a backward perspective. Future research should test the validity of the proposed model in other industries that are transitioning towards greener processes, such as the construction sector. Second, this study used a sample of Spanish manufacturing companies given the experts' call to lessen their environmental footprint. However, climate change should be addressed globally. Therefore, future research should test the validity of the model in other countries and perform cross-country comparisons. In addition, the sample is exclusively composed of MEs. Future research should test whether, in the proposed model, the company size impacts its green process innovation performance. This study focuses on the intra-organizational level. Consequently, future studies could also investigate the impact of REU at the macro level for a systemic transition of the whole manufacturing industry. Indeed, this study suggests that an inter-organizational perspective on REU could enable the adoption of sustainable practices, resource efficiency, and closed-loop systems across supply chains and value networks. Finally, it would be valuable to test our model in other contexts that require organizational flexibility, such as digital transition or green product innovation.

AI statement

During the preparation of this work, the authors used Grammar in order to improve the grammar as none of the authors are native speakers of English. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of interest statement

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

CRediT authorship contribution statement

Juan-Gabriel Cegarra-Navarro: Writing – review & editing, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Laura Di Chiacchio:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Conceptualization. **Clara Cubillas-Para:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Funding acquisition, Conceptualization.

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Appendix 1

Questionnaire items

Regenerative Unlearning: please rate the following statements on a scale from 1 (total disagreement) to 7 (total agreement).
UpMM $_1$: Employees are more willing to adopt new work methods than our competitors. UpMM $_2$: Employees have room to exploit new opportunities. UpMM $_3$: Employees are encouraged to promote new visions, goals and ideas. ChR_1: New routines enable the active participation of employees in generating ideas for new products or services. ChR $_2$: New routines enable the active participation of employees in generating ideas for new production processes or organizational procedures. ChR $_3$: New routines systematize employee experiences. REL_1: The company emphasizes the need to increase the level of competence of employees. REL_2: The company allocates resources to increase employee competence. REL_3: The company encourages employees to learn from their experiences. Source: Adapted from Cegarra-Navarro and Wensley (2019), Makkonen et al. (2014)
Knowledge Breadth: please rate on a scale from 1 (total disagreement) to 7 (total agreement) the following statements
KB_1: Our R&D experience is made up of knowledge from various fields. KB_2: The company tries to increase investments in R&D. KB_3: The company develops routines for the company's R&D. Source: Adapted from Zhou and Li (2012)
Regarding the depth of your company's knowledge of the industry in which your company operates, please rate on a scale from 1 (total disagreement) to 7 (total agreement) the following statements:
KD_1: We are very familiar with this industry. KD_2: We have gained rich experience about this industry. KD_3: Our company is widely known in this industry. KD_4: We have great knowledge about the technology of this industry. Source: Adapted from Zhou and Li (2012)
Green Process Innovation Performance: please rate on a scale from 1 (total disagreement) to 7 (total agreement) regarding the manufacturing processes in which your company has been involved in the last three years:
$GPIP_1$: Effectively reduced the release of hazardous substances or wastes $GPIP_2$: Recycled waste and emissions that allow it to be treated and reused $GPIP_3$: Reduced consumption of water, electricity, coal or oil $GPIP_4$: Reduced use of raw materials Source: Adapted from Chen et al. (2006) and Kawai et al. (2018)

Change routines→ ChR; Update mental models→ UpMM; and Relearn→REL.

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