ANALYZING THE EFFECTS OF KNOWLEDGE MANAGEMENT ON GREEN PRODUCT AND PROCESS INNOVATIONS IN THE FIELD OF PV/T TECHNOLOGIES

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The present paper analyzes the individual effects of three dimensions of knowledge management on product and process innovations in the field of PV/T technologies. Forms of a specially prepared questionnaire were adequately filled in by 300 Serbian companies who already use, produce or plan to produce some PV/T technology. The collected data were analyzed by means of the partial least squares structural equation modeling algorithm in the partial least squares path modeling software package version 0.5.0. The survey was conducted in the period from May to September 2023 in 300 small- and medium-sized companies. The findings show that knowledge acquisition, knowledge storage, and knowledge sharing, as dimensions of knowledge management, have positive effects on the implementation of product and process innovations in the surveyed companies. However, it is revealed that knowledge sharing has the greatest effect on the considered innovations in companies dealing with PV/T technologies. In addition, the lowest effect is obtained for the dimension of knowledge acquisition, while the effect of knowledge storage is medium.

Key words*: knowledge management (KM), knowledge management (KM) dimension, partial least squares structural equation modeling (PLS-SEM) algorithm, product and process innovation (PPI), PV/T technology*

1. Introduction

Two main categories of all existing green innovations are [1]: green product innovation and green process innovation, commonly abbreviated to green PPIs. Green PPIs refer to all forms of product and process innovations which minimize environmental damage and ensure that natural resources are utilized in the most effective manner possible. Such green PPIs certainly include innovations related to the field of photovoltaic/thermal (PV/T) technology. Accordingly, various studies on green innovations have been conducted by other researchers. For example, several recent studies on knowledge management (KM) and innovation capability reveal that the relationship between KM and green innovations leads to sustainable development [2-5]. Furthermore, the relationship between KM and green innovations seems to have multiple conceptualizations. Therefore, this study will examine the relationship between the dimensions of KM (knowledge acquisition, knowledge storage, and knowledge sharing) and green innovations (i.e., green PPIs in PV/T technology).

At the outset, it is essential to clarify why this study focuses on the three specific KM dimensions: acquisition, storage, and sharing. Although the literature often recognizes multiple KM processes, including knowledge creation and application [6,7], this study explicitly investigates these three dimensions because they directly influence the innovation capacity of firms, particularly within small- and medium-sized enterprises. According to Alavi and Leidner [6], the interplay among knowledge acquisition, storage, and sharing processes significantly facilitates innovation by enhancing an organisation's ability to leverage existing knowledge resources efficiently. Furthermore, Tzortzaki and Mihiotis [7] highlight the practical importance of these processes in the context of rapidly changing and highly competitive environments, such as renewable energy sectors. The focus on knowledge acquisition, storage, and sharing is deliberately chosen due to their critical roles in enabling organisations, particularly small- and medium-sized enterprises, to efficiently respond to external environmental pressures, rapidly adopt sustainable innovations, and effectively compete in emerging markets. Although other dimensions such as knowledge creation or application are important, their examination is beyond the scope of this study, as the priority is to explore how organisations systematically handle existing and externally obtained environmental knowledge to enhance green PPIs within PV/T technology. By addressing these aspects, this research not only fills a gap specifically related to PV/T technology but also contributes to broader theoretical discussions on the differentiated impact of KM processes on innovation outcomes.

Study [8] identified that the KM process can contribute to green innovations including its dimensions of acquisition, dissemination and application. The relationship between several dimensions of KM (knowledge acquisition, knowledge conversion, knowledge dissemination, knowledge application, and knowledge reuse) and business model innovation was examined in [9]. The effect of organizational agility on environmental knowledge as an instrument for the development of green innovation in products was analyzed in [10]. Critical roles of green knowledge acquisition in enhancing green KM and green technology innovation activities in improving corporate environmental performance were investigated in [11]. The effects of dimensions of KM (knowledge creation, knowledge acquisition, knowledge sharing, and knowledge application) on green innovation practices were studied in [12]. The effects of information management practices (termed as knowledge acquisition, knowledge dissemination, and knowledge application) on green innovations among small and medium companies in China were examined in [13]. The relationship between green technology implementation and KM process to minimize manufacturing risk was analyzed in [14].

Publications related to past, present, and future of green product innovation were reviewed in [15]. The relationship between green innovation process and KM from the perspective of tools and practices, in the initial stages of the product development process was analyzed in [16]. Publications related to present and future green process innovation were reviewed in [17]. Evidence that internal competencies and the role of buyers in knowledge transfer are critical for describing green PPIs was provided in [18]. Green KM as a novel concept of KM aiming to integrate green aspects into all dimensions of KM was proposed in [19]. Finally, the answer to the question "Does the interaction between the KM process and sustainable development practices boost corporate green innovation?" can be found in [20]. Based on this literature review, analyzing the individual effects of knowledge acquisition, knowledge storage, and knowledge sharing on green PPIs in PV/T technology can be identified as a research gap that has not been addressed so far. The motivation of the authors is to address this gap.

Nowadays, the search for new, original, competitive and genuine green products and green processes has attracted global attention. A number of research studies have been conducted to determine whether KM can enhance green or solar-powered PPIs [1-5,12,18]. According to the literature review carried out, there are no studies whose results indicate that KM may have any negative effect on green PPIs. However, the intensity and speed of climate change may affect researchers and manufacturing companies around the world to rapidly develop new green products and processes at the expense of creativity and quality, which should be of great concern to governments at all levels and industry executives. Such a situation requires special attention and necessary actions in order to eliminate possible negative effects that this may have on the economy of a country. Accordingly, this study will investigate whether proper KM by small- and medium-sized companies in Serbia can enhance green or solar-powered PPIs together with creativity in relation to the required speed of green product development.

This study focuses on small- and medium-sized manufacturing companies due to their crucial role in industrial innovation and sustainability. Unlike larger enterprises, they face resource constraints, limited knowledge access, and regulatory pressures, making green PPIs more challenging to implement. In the PV/T technology sector, these companies struggle with financial and technical limitations, hindering their ability to acquire and manage environmental knowledge. Effective knowledge acquisition, storage, and sharing can help overcome these barriers, enhancing their capacity for sustainable innovation. By examining these key KM dimensions, this study provides insights to support the adoption and integration of green innovations, ensuring competitiveness and compliance with sustainability goals.

Recent literature has emphasized the general positive relationship between KM and PPIs. Nevertheless, a detailed critical examination of how each dimension of KM specifically influences green PPIs, particularly within the context of PV/T technologies, remains limited. Existing studies have often broadly associated KM practices with green innovation without clearly distinguishing between knowledge acquisition, knowledge storage, and knowledge sharing. Addressing this gap provides a stronger theoretical justification for conducting this research. Additionally, the relevance and meaning of the concept "green knowledge" is explicitly clarified. According to Iliescu [21], green knowledge is defined as knowledge oriented towards environmental sustainability, encompassing best practices, innovative technologies, and strategic insights specifically aimed at minimizing ecological impact and promoting efficient use of resources. Within the PV/T industry context, the effective management of green knowledge significantly facilitates companies' capabilities to innovate sustainably, thus enhancing their competitive advantage and their contribution towards broader sustainability goals. Therefore, the study intends to examine the following hypotheses:

- **H1**: The knowledge acquisition has a positive effect on green PPIs.
- **H2**: The knowledge storage has a positive effect on green PPIs.
- **H3**: The knowledge sharing has a positive effect on green PPIs.

2. Development of research questions

A validation of previously defined hypotheses represents the basis for the theory of green KM. Figure 1 shows the corresponding structural model.

In general, knowledge acquisition is the dimension through which knowledge can be secured [22]. According to [23], green knowledge acquisition plays a partial mediating role between green learning orientation and green innovations. Similarly, the study [24] gave a mediating role to green knowledge acquisition in the relationship between international experience and global economic performance. Moreover, knowledge acquisition can contribute to green innovations [8,12,13], business model innovation [9], corporate environmental performance [11], creating a new concept of KM [19], and so on. Furthermore, the acquisition of green technical, market and product knowledge helps manufacturing companies to effectively develop their strategic, tactical and internal green market orientations to build their green innovation capability [25].

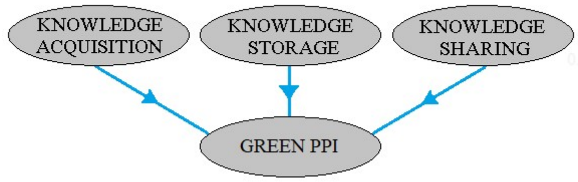

Fig. 1 Structural model

Knowledge storage as a dimension of KM has been recognized by a large number of researchers [22]. In addition, green knowledge storage together with green knowledge acquisition serves as the basis for development and validation of the green KM scale to understand how effectively companies adhere to green KM practices in their operations [19]. According to [26], *Bartezzaghi et al.* in 1997 suggested that knowledge storage is a fundamental lever for stimulating innovation. This can certainly be generalized to the case of green or solar-powered innovations related to PV/T technology. Moreover, knowledge storage has a favorable effect on innovation implementation ability [8], refers to the mechanisms that can store and retrieve all kinds of data, information and knowledge [27], etc.

Some researchers have conceptualized knowledge sharing as a dimension of KM that can enhance the development of manufacturing companies and the creation of new and innovative ideas through proper KM [22]. The effect of knowledge sharing on green innovation practices in [12] was identified as positive. In [28], external knowledge sharing practices were found to strongly affect green innovation performance. Knowledge sharing is also connected with applications of that knowledge and enables workers to practice their knowledge [19]. In this regard, study [19] also highlighted the importance of green knowledge sharing for green innovation. Green knowledge sharing together with research and development was identified in [5] as critical for innovations. Moreover, green knowledge sharing shapes green innovation ideas and effectively implements green innovation plans in manufacturing companies [29]. Furthermore, manufacturing companies and their staff members can only be positively affected by green knowledge sharing [30].

In addition to the individual dimensions of KM, the demographic characteristics of companies can also affect the green PPIs. The demographic characteristics used in [31] to identify the green consumer were age, gender, income, level of education, and occupation. In addition to this, some studies found that the perception of consumers is a better predictor of green innovation adoption than demographic characteristics such as income, education and age [32]. Age, gender, income, level of education, occupation, social class and some other socio-demographic variables were amongst the key demographic characteristics that have been used in segmenting and profiling green consumers [33]. Moreover, a questionnaire designed to assess the relationship between KM and the performance of medium-sized and large companies included the following demographic characteristics [34]: company size, lifespan of the company, manager's experience, manager's qualifications, and manager's job title. Furthermore, the study [35] tested if knowledge sharing correlates with demographic characteristics in the case of hospitals and other healthcare organizations. Accordingly, very few studies deal with the effects of demographic characteristics of companies on the green PPIs compared to those dealing with the effects of demographic characteristics in general on green consumers. Therefore, the demographic characteristics of companies to be considered in this paper are as follows: type and status of companies, number of employees, management position of employees, level of education, age and gender of employees, and years of work experience. Therefore, the effects of the knowledge acquisition, knowledge storage, and knowledge sharing on the green PPIs of manufacturing companies can only be positive. Whilst the effects of demographic characteristics on the green PPI of manufacturing companies are different and cannot all be considered as only positive or only negative.

In order to analyze the effects of the individual dimensions of green KM (i.e., the perception of corporate social responsibility from an ecological aspect) and the demographic characteristics on the organizational performance of manufacturing companies, the following research questions are formulated:

- **Q1**: Which of the individual dimensions of KM has the greatest effect on the green PPIs?
- **Q2**: Are there differences between the effects of the individual dimensions of KM on the green PPIs?

3. Research methodology

According to [36], when the sample size is smaller and when the objective of structural modeling is to predict and explain the outcome factors as acquired by the in-sample and out-of-sample metrics, the partial least squares – structural equation modeling (PLS-SEM) algorithm can be used. Specifically, the PLS-SEM algorithm iterates backward and forward multiple times optimizing first a measurement model and then a structural model, and then again the measurement and structural models, and so on [36]. The iteration procedure continues until the ultimate objective of optimizing prediction, rather than model fit, is achieved. The possibility of obtaining solutions with smaller sample sizes is the result of applying partial least squares to data analysis [36]. Consequently, the size of the considered sample required the application of the PLS-SEM algorithm in this paper.

As suggested in [36], structural equation modeling was used to test hypotheses (H1, H2 and H3) about relationships between indicators and factors. Indicators are referred to as measured or observed variables, while factors (which cannot be measured directly) are referred to as latent or unobserved variables. In addition, the SEM consists of two models known as the measurement and structural models. Creating any theory-based model and testing the initially created model may not make sense unless the measurement model is valid. Therefore, researchers usually test the measurement model before the structural one. The considered structural model is shown in Figure 1.

The sample on which the confirmatory analysis is performed consists of 300 randomly selected respondents, that is, 300 small- and medium-sized manufacturing companies from Serbia. The sample selection was conducted using a systematic random sampling method, where companies were chosen at regular intervals from a structured industry database. This approach ensured that every company had an equal probability of being selected while maintaining proportional representation across different manufacturing sectors. The questionnaire design was based on pre-validated scales from two widely recognized studies: the green KM scale by [19] and the green technology and innovation scale by [37]. These scales have been used in prior research, ensuring reliability and construct validity. Each survey item was carefully adapted to align with the context of small- and medium-sized manufacturing companies involved in PV/T technology. To further verify the instrument's reliability, Cronbach's alpha and Rho coefficients were calculated, confirming internal consistency across all constructs. In this research, a survey with a total of 31 questions was conducted in the period from May to September 2023. The questions are divided into two groups. The first group of questions consists of questions of a demographic nature, while the second group includes questions related to attitudes towards the topics covered by the research.

The first group of questions includes company type, company status, number of employees, position and level of education of the management staff, gender, age, and years of work experience. Respondents answered these eight questions by circling the appropriate option. In addition to this, respondents answered the questions from the second group by choosing a number on a scale from 1 to 5, where 1 indicates the lowest intensity, and 5 the highest intensity. The survey contained 23 such questions and they are the subject of PLS-SEM analysis. As a research instrument, the survey used was created by combining two relevant questionnaires from [19,37], namely: one questionnaire on green KM [19] and another one on green technology and innovation [37]. Table 1 shows the group of questions related to demographic data of the sample.

Univariate extreme values are identified via box plots for each variable, and the Cook's distance measure is used to identify multivariate extreme values. The univariate normality for each indicator and factor is assessed using the Kolmogorov-Smirnov and Shapiro-Wilk tests. To test the hypotheses, PLS path analysis is applied, which is performed with the programming language R version 4.3.1 in the PLS-PM software package version 0.5.0. Additionally, to clarify the usage of the PLS-PM software, it is important to highlight that this software package was specifically chosen for its effectiveness in handling smaller sample sizes and its ability to focus on optimizing prediction rather than model fit. PLS-PM is particularly beneficial for predictive and explanatory modeling, which aligns well with the objectives of this research. It allows for a more robust analysis of the complex relationships between KM processes and green PPIs, ensuring that the results are both reliable and practical in real-world settings. Further details on the application of PLS-SEM in research can be found in [36], which provides comprehensive guidelines for using the technique in various fields, including education and second language research. As detailed in reference [38], an extensive overview of the theory and practical application of PLS-SEM is provided, including key considerations for software selection and the interpretation of results. The guidelines in this reference further clarify how PLS-SEM can be utilized effectively, especially in studies with small sample sizes, such as this research.

The validity and discriminativeness of the variables (indicators and factors) are examined by means of the Cronbach's alpha and Rho coefficients [39], that is, by comparing the loading of each variable with its own loading and loadings of other variables (so-called crossloadings). It is assumed that all indicators are unidimensional, i.e., to measure the same factor (latent variable). Finally, the model is validated using the Bootstrap validation method.

Table 1. Demographic statistics of the sample

Variable	Option	Number, N	Percentage
Company type	1 – Processing industry	77	25.7
	2 – Services	151	50.3
	3 – Others	72	24
Company status	1 – Public	26	8.7
	2 – Private	272	90.7
	3 – Mixed	2	0.7
Number of employees	≤10	213	71
	11-50	28	9.3
	51-250	39	13
	>250	20	6.7
Management position	Senior	209	69.7
	Middle	77	25.7
	Junior	14	4.7
Education level	Secondary	28	9.3
	Undergraduate	103	34.3
	Graduate	102	34
	Postgraduate	67	22.3
Age	≤29	33	11
	30-44	151	50.3
	45-54	108	36
	≥55	8	2.7
Gender	Male	213	71
	Female	87	29
Years of work experience	≤5	43	14.3
	6-15	142	47.3
	16-25	100	33.3
	≥26	15	5

Indicators (i.e., measured variables) and factors (i.e., latent variables) are based on the attitudinal questions (i.e., items of measurement) related to the perception of the impacts of the knowledge acquisition (KAC1, KAC2, KAC3, KAC4, and KAC5), knowledge storage (KST1, KST2, KST3, KST4, and KST5), and knowledge sharing (KSH1, KSH2, KSH3, KSH4, KSH5, and KSH6) on the innovation of green products and processes (GPPI1, GPPI2, GPPI3, GPPI4, GPPI5, GPPI6, and GPPI7). The internal consistency of the items included in the measured and latent variables is examined by calculating the Cronbach's alpha coefficient [39]. The number of items included in the variables is N'=23. Table 2 lists the measured and latent variables together with the corresponding items used in this paper.

4. Results and discussion

4.1. Descriptive statistics

Based on the Cook's distance measure, eight multivariate extreme values are identified and excluded from further analysis. In this way, the final sample on which the confirmatory analysis is performed is reduced to 292 respondents. Multivariate extreme values are shown in Figure 2. In addition, there are no missing data in the data related to these 292 respondents.

For each indicator and factor, a univariate normality test is performed using the Kolmogorov-Smirnov and Shapiro-Wilk tests. The results of these tests and descriptive statistics of the indicators and factors are given in Table 3. It is obvious from Table 3 that no indicator or factor is normally distributed.

Table 2. Indicators, factors and attitudinal questions from the KM scale

Dimension, indicator or factor	Attitudinal question
Knowledge acquisition	–
KAC1	Company regularly receives information about environmentally friendly products and processes from external stakeholders (e.g. customers and suppliers)
KAC2	Company regularly receives information about environmentally friendly products and processes from internal stakeholders (e.g. management and staff)
KAC3	Company regularly organizes trainings for employees to develop their knowledge about environmentally friendly products and processes
KAC4	Company has a well-developed information system through which employees can get the necessary information
KAC5	Company encourages and supports employees to acquire knowledge about environmentally friendly products and processes
Knowledge storage	–
KST1	Company has sufficient information about environmentally friendly products and processes
KST2	Company has an excellent information system for managing information related to environmentally friendly products and processes
KST3	Information about a specific problem is easily available through our information system
KST4	We have comprehensive information about our competitors and the environmental impact of their operations
KST5	Even if someone leaves the company, our information system retains their knowledge
Knowledge sharing	–
KSH1	Employees in our company regularly communicate with each other in order to exchange knowledge and discuss further directions for the development of environmental protection
KSH2	Company has a well-organized system through which knowledge can be shared and through which one can learn from each other in an affirmative
KSH3	Company has provided the latest equipment and technology for the acquisition and exchange of knowledge
KSH4	Company recognizes and rewards employees who share innovative ideas and information to improve environmental protection processes
KSH5	Company regularly shares the latest environmental knowledge and market trends with its employees through e-mails, trainings and workshops
KSH6	Company regularly shares information and knowledge related to the natural environment with our customers, suppliers and other stakeholders
Innovation of green products and processes	Has your company ever taken the following actions when designing products or processes?
GPPI1	Environmentally friendly materials (for instance, less polluting or non-polluting/less toxic or non-toxic materials)
GPPI2	Improvement and design of environmentally friendly packaging (for instance, less consumption of paper and plastic) for existing and new products
GPPI3	Recycling, reuse and processing of materials at the end of a product's life
GPPI4	Eco-labelling
GPPI5	Lower energy consumption from sources such as water, electricity, gas and gasoline during production/use/disposal
GPPI6	Cleaner technologies for saving energy, water, etc. and pollution prevention
GPPI7	Reduction or complete elimination of toxicity in the production process

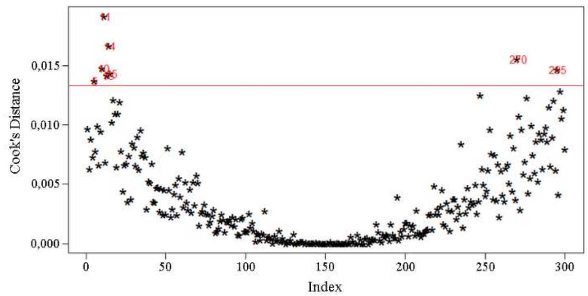

Fig. 2 Multivariate extreme values

Table 3. Results of the Kolmogorov-Smirnov and Shapiro-Wilk tests and descriptive statistics of the indicators and factors

Indicator or factor	Kolmogorov-Smirnov test		Shapiro-Wilk test		Kurtosis	Skewness	Mean	Std. dev.
	Test statistic	*p*-value	Test statistic	*p*-value				
Knowledge acquisition								
KAC1	0.950	<0.001	0.856	<0.001	2.227	0.526	2.925	1.065
KAC2	0.977	<0.001	0.814	<0.001	1.856	0.491	3.062	1.085
KAC3	0.977	<0.001	0.824	<0.001	2.272	0.608	2.945	0.954
KAC4	0.977	<0.001	0.866	<0.001	1.765	0.115	3.411	1.072
KAC5	0.943	<0.001	0.860	<0.001	2.314	-0.449	3.305	0.995
Knowledge storage								
KST1	0.957	<0.001	0.899	<0.001	2.280	-0.044	3.425	1.028
KST2	0.957	<0.001	0.898	<0.001	2.401	0.051	3.188	0.950
KST3	0.957	<0.001	0.892	<0.001	2.550	0.250	3.116	0.949
KST4	0.898	<0.001	0.905	<0.001	2.400	0.298	2.897	1.095
KST5	0.888	<0.001	0.896	<0.001	2.037	-0.233	3.366	1.265
Knowledge sharing								
KSH1	0.953	<0.001	0.882	<0.001	1.805	0.029	3.298	1.147
KSH2	0.977	<0.001	0.875	<0.001	1.889	-0.049	3.572	1.018
KSH3	0.960	<0.001	0.876	<0.001	1.807	0.041	3.277	1.110
KSH4	0.936	<0.001	0.871	<0.001	1.710	0.065	3.205	1.212
KSH5	0.844	<0.001	0.909	<0.001	1.975	-0.099	3.041	1.243
KSH6	0.868	<0.001	0.887	<0.001	2.160	-0.325	2.990	1.079
Innovation of green products and processes								
GPPI1	0.939	<0.001	0.860	<0.001	3.089	-0.775	3.723	1.043
GPPI2	0.939	<0.001	0.712	<0.001	4.225	-1.311	3.712	0.948
GPPI3	0.939	<0.001	0.857	<0.001	3.596	-0.796	3.671	0.960
GPPI4	0.939	<0.001	0.898	<0.001	2.549	-0.398	3.507	1.053
GPPI5	0.939	<0.001	0.900	<0.001	2.719	-0.304	3.394	0.994
GPPI6	0.939	<0.001	0.872	<0.001	3.004	-0.615	3.476	0.968
GPPI7	0.939	<0.001	0.892	<0.001	2.707	-0.468	3.490	1.020

4.2. Correlations among variables

The correlation matrices of the inductors for the dimensions of knowledge acquisition, knowledge store and knowledge sharing are given in Tables 4, 5 and 6, respectively. Table 7 presents the correlation matrix of the factors for the dimension of green PPIs.

According to Table 4, there is a very strong positive correlation between the indicators KAC1 and KAC2, as well as a strong positive correlation between the indicators KAC2 and KAC3. The other indicators related to the knowledge acquisition correlate positively and weakly to moderately.

Based on Table 5, it can be seen that the correlations between the indicators KST2 and KST4 and between the indicators KST2 and KST5 are positive and very weak. Correlations between the other indicators of the knowledge storage dimension are positive and moderate.

According to Table 6, there are strong positive correlations between the indicators KSH1 and KSH2 and between the indicators KSH5 and KSH6. The remaining correlations related to the knowledge sharing dimension are positive and moderate to moderately strong.

From Table 7, it follows that all correlations between the indicators of the dimension of green PPIs are positive and moderately strong.

Table 4. Correlation matrix of the indicators related to the knowledge acquisition

Indicator	KAC1	KAC2	KAC3	KAC4
KAC2	0.904			
KAC3	0.574	0.603		
KAC4	0.352	0.450	0.166	
KAC5	0.310	0.418	0.510	0.327

Table 5. Correlation matrix of the indicators related to the knowledge storage

Indicator	KST1	KST2	KST3	KST4
KST2	0.453			
KST3	0.375	0.536		
KST4	0.280	0.048	0.276	
KST5	0.467	0.080	0.299	0.550

Table 6. Correlation matrix of the indicators related to the knowledge sharing

Indicator	KSH1	KSH2	KSH3	KSH4	KSH5
KSH2	0.851				
KSH3	0.488	0.476			
KSH4	0.601	0.498	0.649		
KSH5	0.584	0.435	0.517	0.624	
KSH6	0.482	0.337	0.504	0.516	0.907

Table 7. Correlation matrix of the factors related to the innovation of green products and processes

Factor	GPPI1	GPPI2	GPPI3	GPPI4	GPPI5	GPPI6
GPPI2	0.742					
GPPI3	0.612	0.805				
GPPI4	0.569	0.745	0.756			
GPPI5	0.659	0.558	0.615	0.714		
GPPI6	0.611	0.561	0.583	0.460	0.540	
GPPI7	0.725	0.590	0.554	0.558	0.717	0.747

4.3. PLS path analysis

Based on the structural model from Figure 1, the paths for analyzing the effects of the acquisition, storage and sharing of knowledge on the green PPIs are defined. The hypotheses H1, H2 and H3 are tested using the PLS path analysis according to Table 8. Table 8 links the hypotheses with the corresponding paths in the considered structural model.

Figure 3 shows the measurement model. Due to the insufficient level of description of some items by the factors underlying them (i.e., item-to-dimension loadings), indicators KAC4, KST2 and KST3 were excluded from the measurement model, so the analysis continued without those indicators.

Table 8. Hypotheses and paths in the considered structural model

Hypothesis	Path
H1	Knowledge acquisition → green PPI
H2	Knowledge storage → green PPI
H3	Knowledge sharing → green PPI

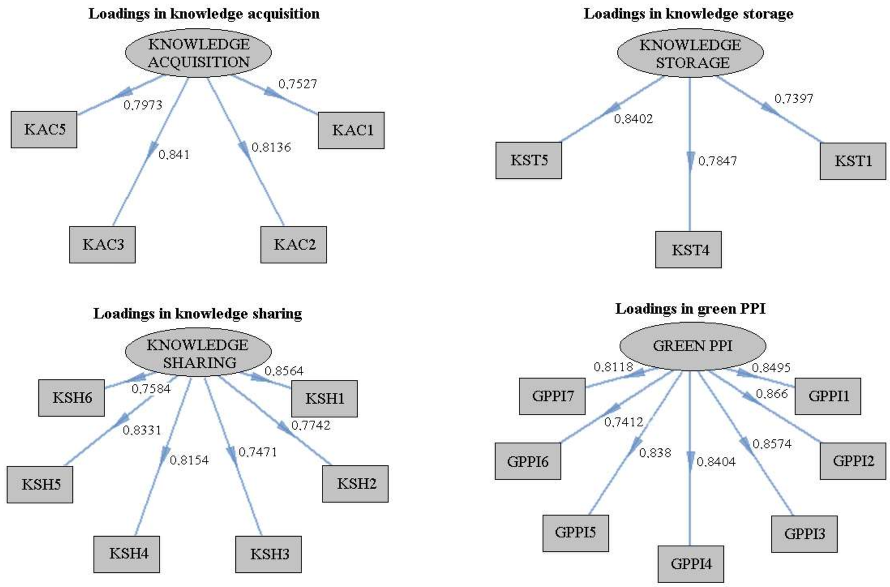

Fig. 3 Measurement model

By comparing the loading of each indicator or factor with its own loading and loadings of other indicators and factors (i.e., crossloadings), the validity and discriminativeness of the indicators and factors are examined. Table 9 gives the results of the examining the validity and discriminativeness of the indicators and factors, namely: Cronbach’s alpha coefficient, Rho coefficient, and average variance extracted (AVE).

Table 9. Results of the examining the validity and discriminativeness of the indicators and factors

Dimension	Cronbach’s alpha coefficient	Rho coefficient	AVE
Knowledge acquisition	0.832	0.890	0.643
Knowledge storage	0.696	0.832	0.623
Knowledge sharing	0.886	0.914	0.638
Green PPI	0.925	0.940	0.689

Based on the measurement model and the examining the validity and discriminativeness of the variables, it is evident that all indicators are unidimensional and that they measure the same factor. Since the Cronbach's alpha coefficient is approximately equal to or greater than 0.7 for all dimensions, it means that the internal consistency of the scale is acceptable. According to Table 9, only in the case of the knowledge storage dimension, the Cronbach's alpha coefficient is close to the threshold of acceptable consistency, while the values of this coefficient for the other dimensions are significantly above the given threshold. In addition, the minimum recommended AVE is 0.5 and all the corresponding AVE values from Table 9 are greater than 0.5. This indicates that more than 50% of the variance of the indicator for a given factor is shared, that is, caused by the impact of the factor, and not by chance.

Table 10 shows the matrix of correlation coefficients between the considered dimensions calculated on the basis of the scores obtained by applying PLS regression.

Table 10. Matrix of correlation coefficients between the considered dimensions

Dimension	Knowledge acquisition	Knowledge storage	Knowledge sharing
Knowledge storage	0.675		
Knowledge sharing	0.392	0.575	
Green PPI	0.431	0.556	0.687

According to Table 10, the correlation between the dimensions of knowledge acquisition and knowledge storage, as well as between the dimensions of knowledge sharing and green PPIs, is positive and moderately strong. In addition, the correlation between the dimensions of knowledge storage and knowledge sharing, as well as between knowledge storage and green PPIs, is moderate. While the correlations between the dimension of knowledge acquisition, on the one hand, and the dimensions of knowledge sharing and green PPIs, on the other hand, are positive and weak.

The loadings of the variables (indicators and factors) for each dimension are given in Figure 4. While these loadings together with the crossloadings of the variables for each dimension are shown in Figure 5. The results from Figure 4 show that all indicators and factors are loaded to a level that is greater than 0.7. In addition, from Figure 5, it is obvious that the variables are distributed by dimensions so that each variable has a higher loading (its own correlation coefficient) than its corresponding crossloadings. This means that the quality of the measurement model is confirmed, that the results from Figure 5 are in support of discriminant validity, and that the considered dimensions are well differentiated from each other. Moreover, according to Figures 4 and 5, the loading is also greater than 0.5 for each variable. This means that in each of the variables there is a hidden factor that explains more than 50% of the variations in the respondents' responses to the questions.

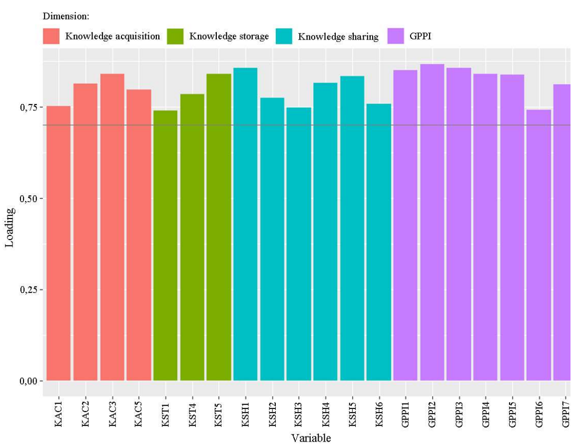

Fig. 4 Loadings of the variables for each dimension

Fig. 5 Loadings and crossloatings of the variables for each dimension

For the assumed structural model, the following correlation strengths are obtained: 0.0952 - for the path between the dimensions of knowledge acquisition and green PPI, 0.1833 - for the path between the dimensions of knowledge storage and green PPI, and 0.5426 - for the path between the dimensions of knowledge sharing and green PPI. Accordingly, the correlation between the dimensions of knowledge sharing and green PPI has the highest strength. The predictive capabilities of the structural model are summarized in Table 11. In Table 11, the quality of the structural model is assessed by means of the coefficient of determination R^2, while the predictive capability of the model is indicated by means of the redundancy index.

Table 11 shows that the structural model well represents the dimensions of the indicators knowledge acquisition (64.9%), knowledge storage (62.3%) and knowledge sharing (63.8%), and that it is the best when it comes to the dimension of the factors GPPI (68.9%). Redundancy index is a measure of the percentage of variance in an endogenous variable explained by its exogenous variables. This index indicates the ability of a set of exogenous variables to explain variation in an endogenous variable.

Accordingly, it can be seen from the column Redundancy index that the exogenous variables contribute to the explanation of the variations of the endogenous variable with only 35.6%.

As there are no inferential tests for the GoF index (i.e., Goodness-of-Fit) in the PSL analysis, it is a pseudo Goodness-of-Fit measure that takes into account the quality of the models, both structural and measurement models [40]. According to [40], the GoF index is calculated as the geometric mean of the average dimension communality and the average R^2 value. The GoF index for the overall model is found to be 0.582, which is less than the threshold of 0.7 that usually indicates high predictive capability. As a measure of Goodness-of-Fit for the models, the R^2 value (which is found to be 0.517) gives a similar indication of predictive capability. Table 12 quantifies the total and partial impacts of the exogenous variables on the endogenous variable. According to Table 12, all exogenous variables from the dimensions of knowledge acquisition, knowledge storage and knowledge sharing have positive impacts on the endogenous variables from the dimension of green PPI. The analysis showed that the greatest impact on the green PPI dimension has the knowledge sharing dimension, where each percentage increase in knowledge sharing leads to an increase in green PPIs by 0.543%.

The model parameters are validated using the bootstrap path coefficients. Table 13 outlines the bootstrap path coefficients calculated. In Table 13, "Original" indicates the original value of the parameters, "Mean boot" the bootstrap mean value, "Std. error" the bootstrap standard error, "Perc.025" the lower percentile (i.e., 2.5%) of the 95% bootstrap confidence interval, and "Perc.975" the upper percentile (i.e., 97.5%) of the 95% bootstrap confidence interval. Table 13 shows that none of the confidence intervals includes zero, which means that all considered paths are statistically significant.

Table 11. Predictive capabilities of the structural model

Dimension	Type of variable	R^2	Communality	Redundancy index
Knowledge acquisition	Exogenous	0	0.649	0
Knowledge storage	Exogenous	0	0.623	0
Knowledge sharing	Exogenous	0	0.638	0
Green PPI	Endogenous	0.517	0.689	0.356

Table 12. Total and partial impacts of the exogenous variables on the endogenous variable

Path	Direct impact	Indirect impact	Total impact
Knowledge acquisition → green PPI	0.095	0.000	0.095
Knowledge storage → green PPI	0.183	0.000	0.183
Knowledge sharing → green PPI	0.543	0.000	0.543

Table 13. Bootstrap path coefficients

Path	Original	Mean boot	Std. error	Perc.025	Perc.975
Knowledge acquisition → green PPI	0.095	0.105	0.060	0.009	0.219
Knowledge storage → green PPI	0.183	0.179	0.080	0.034	0.334
Knowledge sharing → green PPI	0.543	0.542	0.045	0.439	0.620

4.4. Results and hypotheses testing

Based on the values of the bootstrap path coefficients, the results of testing the research hypotheses are summarized as follows: (i) The hypothesis that the knowledge acquisition has a positive effect on the green PPI (Hypothesis H1) is confirmed and supported by the results. (ii) The hypothesis that the knowledge storage has a positive effect on the green PPI (Hypothesis H2) is confirmed and supported by the results. (iii) The hypothesis that the knowledge sharing has a positive effect on the green PPI (Hypothesis H3) is confirmed and supported by the results.

5. Conclusion

Based on the obtained results and discussion, the following conclusions can be drawn: (**i**) It was revealed that the knowledge sharing has the greatest positive effect on the green PPIs related to PV/T technology. This is the response to the first research question. (**ii**) It was shown that each percentage increase in the knowledge sharing leads to an increase in the green PPIs related to PV/T technology by 0.543%. (**iii**) It was found that the dimensions of knowledge acquisition, knowledge storage, and knowledge sharing have a positive effect on the green PPIs of the considered companies. In addition to the fact that knowledge sharing has the greatest effect, it was found that knowledge acquisition has the lowest effect, and that knowledge storage has a medium effect. This is the response to the second research question. (**iv**) It was shown that the knowledge acquisition, knowledge storage and knowledge sharing contribute to the explanation of the variations in the green PPIs related to PV/T technology with only 35.6%. (**v**) It was found that the GoF index is 0.582 and can be used to assess the predictive capability of the model. (**vi**) It was determined that the R^2 value is 0.517 and that it can be used to evaluate the predictive capability of the model in the same manner as the GoF index.

These findings have both theoretical and practical implications. The study contributes to the KM and innovation literature by demonstrating how knowledge-sharing mechanisms significantly enhance green innovations in PV/T technology. Practically, the results emphasize the importance of developing knowledge-sharing platforms, training programs, and collaborative networks to accelerate green innovation among manufacturing companies. Policymakers and industry leaders should prioritize knowledge-driven strategies to foster sustainable technological advancements. While this study provides valuable insights, several limitations must be acknowledged. The sample is limited to small- and medium-sized manufacturing companies in Serbia, which may affect the generalizability of the results to other industries or geographical regions. Additionally, the study focuses on three KM dimensions (acquisition, storage, and sharing) but does not include knowledge creation or application, which could further influence green innovation outcomes. Moreover, the reliance on self-reported data introduces the potential for response bias.

Future research should expand the scope by incorporating additional KM dimensions and exploring the impact of digital transformation, artificial intelligence, and external knowledge networks on green innovation. Comparative studies across industries and longitudinal analyses could provide deeper insights into the long-term impact of KM on sustainable innovation in PV/T technology and beyond.

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Paper submitted: 06.12.2024

Paper revised: 12.03.2025

Paper accepted: 19.03.2025