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The Role of Knowledge Management in Driving Sustainable Development in Serbia's Green Economy

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This study develops a conceptual framework to investigate the role of knowledge management in facilitating Green Product and Process Innovations (GPPI) within the broader context of sustainable business development. While existing literature recognizes the strategic importance of knowledge management, it offers limited insight into its specific contribution to achieving sustainability-related outcomes. To address this gap, a cross-sectional research design was employed. Data were collected through a structured survey administered to 300 respondents, comprising lower, middle, and upper-level managers from small, medium, and large manufacturing, service, and hybrid organizations in Serbia. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM)..The results reveal that Knowledge Management (KM) exerts a positive and statistically significant influence on Green Product and Process Innovations. Specifically, key Knowledge Management processes - such as knowledge dissemination and application - emerge as significant drivers of green innovation. These innovations, in turn, positively affect various dimensions of sustainability metrics, including environmental outcomes, economic efficiency, and managerial commitment to environmental protection. The statistical results (β significant at $p < 0.001$) confirm the robustness of these relationships. R^2 values indicate moderate to high levels of explained variance, while f^2 and Q^2 values confirm the predictive relevance of the model. These findings provide empirical support for the theoretical proposition that Knowledge Management plays a pivotal role in promoting green innovation capabilities. The originality of this study lies in its examination of previously underexplored, multidimensional interrelationships among Knowledge Management processes, green innovations, and Sustainable Development (SD). The observed positive correlations between these constructs further reinforce the validity of the proposed conceptual framework.

Keywords: Environmental protection, Green product and process innovation, Knowledge management, Structural equation modeling, Sustainable development

Introduction

Organizations today face rapid technological, social, and environmental changes. The rise of the Internet has removed geographic barriers, enabling consumers to access global suppliers and choose competitive alternatives.[1] Concurrently, firms face increasing pressure to adopt sustainable practices, with knowledge recognized as a critical strategic resource.[2] Effective knowledge acquisition, sharing, and application enhance innovative capabilities and support adaptation to sustainability challenges. Among these, Green Product and Process Innovations (GPPI) link Knowledge Management (KM) to sustainable development, encompassing product and process modifications that reduce environmental impact while sustaining economic performance.[3,4] Despite growing research, the literature remains fragmented, with key limitations still unaddressed.

Most prior studies treat Knowledge Management (KM) as a single construct, overlooking its dimensions (acquisition, sharing, application) and relying on linear, single-theory models—primarily RBV—with little evidence from developing economies, particularly the Western Balkans. To address these gaps, this study develops a multidimensional SEM framework, conceptualizing KM as interrelated capabilities and linking them to green innovation and sustainable performance (ENVP, ECOP), while accounting for mediating and moderating effects. The model is tested via PLS-SEM, enabling analysis of reflective and formative constructs with robust diagnostics (R^2, f^2, Q^2, t-values).

The theoretical framework integrates RBV and Dynamic Capabilities (DC) theory: RBV highlights

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knowledge as a valuable, rare, non-substitutable asset for competitive advantage, according to Barney[5], while DC emphasizes adaptive resource reconfiguration.[6] KM is thus positioned as both a strategic resource and a dynamic capability driving green innovation and sustainable transformation.

This approach frames Knowledge Management (KM) as both a source of competitive advantage and a mechanism for environmental adaptation, highlighting its dual role in enhancing organizational sustainability and green innovation. Guided by this framework, the study addresses a key question: To what extent, and through which mechanisms, does KM influence green product and process innovations within organizations? This question forms the basis for the proposed hypothesis:

- H1: Knowledge management positively influences Green Product and Process Innovations (GPPI).
- H2: GPPI positively contributes to sustainable development in enterprises.
- H3: Knowledge management directly supports sustainable development outcomes.
- H4: Knowledge management mediates the relationship between GPPI and sustainable development.

Sample Analysis

The research was conducted in collaboration with the Technical Faculty in Bor, from May to September 2023, involving 300 small and medium-sized manufacturing enterprises in Serbia.[7] Detailed data on the demographic profile of respondents were obtained based on eight questions covering organizational characteristics (Table 1).The final sample consisted of 300 valid responses**,** which provides a sufficient statistical basis for SEM, where a sample size of 200 or more is typically recommended for models of moderate complexity. The sample is statistically valid and diverse across key characteristics:

- Respondents come from various industry sectors, including processing (25.7%), services (50.3%), and others (24%).
- The dominant share of respondents (90.7%) comes from private sector organizations**,** which reflects the typical structure of economies in transition.
- The majority of participants have higher education (34.3% undergraduate, 34% graduate, 22.3% postgraduate) and significant work experience, with 47.3% having 6–15 years and 33.3% having 16–25 years.
- More than 50% of respondents are between 30 and 44 years old, which indicates a balanced representation of mid-career professionals.

The sample is reliable for analyzing knowledge management and green innovation. However, two potential response biases should be noted. First, micro enterprises (≤10 employees) comprise 71% of the sample, reflecting regional economic structure but potentially limiting generalizability to larger firms. Firm size should be controlled, and future studies could use more balanced samples or multi-group analysis. Second, senior managers account for 69.7% of respondents, which may bias results toward strategic perspectives, under representing middle- and junior-level insights.

The sample shows a gender imbalance, with 71% male and 29% female respondents. Regarding work experience, 47.3% have up to 15 years, 33.3% between 16 and 26 years, and the remainder over 26 years. A strong correlation is observed between age and experience: most respondents are under 44, aligning with the largest share of those reporting up to 15 years

Table 1 — Comparison of previous models and the proposed multidimensional SEM approach

Element	Previous Models	Proposed Model
Approach to KM	Treated as a single or aggregate latent variable	Operational zed through a multidimensional construct (e.g., acquisition, sharing, application)
Link to GPPI	Direct effects, often between overall KM and GPPI	Multiple paths: KM dimensions → green products + green processes
Model type	Regression, CB-SEM with a few latent variables	Multidimensional PLS-SEM with reflective/formative indicators
Theoretical foundation	Typically, RBV or DC (separately)	Integrated RBV + DC framework
Included factors	Few factors, usually no mediators/moderators	Includes mediators (e.g., sustainability) and moderators (e.g., adaptive capacity)
Statistical measures	Mostly R^2 and p-values	R^2, f^2, Q^2, t-values
Explained variance (R^2)	Medium: 0.25 – 0.35	Higher: e.g., $R^2 = 0.524 – 0.724$
Predictive relevance (Q^2)	Rarely reported	Calculated: $Q^2 = 0.29$
Managerial implications	Limited guidance	Concrete strategies for KM and green innovation development

of work experience. As age increases, years of experience rise accordingly.

Literature Review and Hypothesis Formulation

This study proposes a conceptual model that integrates KM, GPPI, and Sustainable development (SD), grounded in the Resource-based view (RBV), Triple bottom line (TBL), stakeholder theory, and ecological modernization theory.

The impact of knowledge management on green product and process innovations

Knowledge management (KM) refers to the structured processes of identifying, acquiring, disseminating, and applying knowledge to improve organizational decision-making and stimulate innovation. Extant literature consistently highlights knowledge as a strategically valuable resource, particularly in driving innovation-related activities. Accordingly, KM is viewed as a critical enabler of an organization's innovation capabilities.[8] Effective KM practices - especially those related to knowledge acquisition, application, and sharing - have been shown to enhance innovation performance, according to Hamdoun *et al.*[9], and contribute to both internal efficiency and external competitiveness.[10] Empirical evidence further supports these claims: a study of a Jordanian consulting firm confirmed a positive relationship between KM and innovation outcomes.[11] Similarly, according to Stanovcic et *al.*[12]emphasize the strategic alignment of KM processes with innovation goals - especially those aimed at ecological and green innovations.

Rooted in the RBV, KM is seen as a fundamental intangible asset that facilitates the development of environmentally sustainable innovations. Knowledge resources, when effectively managed, can support organizations in designing green products and optimizing processes to reduce environmental impacts.

Based on theoretical foundations and empirical insights, the following hypothesis is proposed:

H1: ***Knowledge management has a positive impact on green product and process innovations.***

Knowledge Acquisition

Knowledge Acquisition (KA) refers to the process through which organizations obtain new knowledge from both internal and external sources in order to enrich their knowledge base and enhance innovation capacity. Prior literature emphasizes that acquiring knowledge - whether from within or outside the organization - reshapes employees' cognitive structures and supports value creation, particularly through new product development and innovation performance.[13] Knowledge Acquisition encompasses an organization's ability to identify, absorb, and integrate new knowledge - an essential capability for effective organizational functioning.[14] However, the relationship between KA and firm performance is not uniformly positive. Some empirical studies suggest that KA alone may not significantly enhance performance unless supported by strategic investments in research and development (R&D), which can stimulate idea generation and indirectly drive innovation.[15] Conversely, other studies underline the centrality of KA in building organizational capacity, fostering innovative behavior, and improving adaptability to technological and market shifts.[16]

Nonetheless, methodological concerns must be acknowledged. In non-experimental structural equation models (SEM), potential endogeneity - particularly reverse causality - may arise, whereby innovative organizations are more likely to engage in proactive knowledge-seeking. Additionally, the effect of KA on innovation may be mediated by subsequent knowledge processes such as dissemination and application.

Drawing upon theoretical insights and empirical evidence, the following hypothesis is proposed:

H1a: ***Knowledge acquisition has a positive impact on innovations in green products and processes.***

Knowledge Dissemination

Knowledge dissemination (KD) refers to the internal flow of knowledge through sharing and gathering mechanisms aimed at enhancing coordination and supporting innovation. It involves two key dimensions: *knowledge sharing*, which makes knowledge accessible to others, and *knowledge gathering*, which involves collecting knowledge from organizational members.[17] These activities are facilitated through both formal and informal channels, such as meetings, collaborative discussions, internal networks, and partnerships. Knowledge Dissemination contributes to various performance outcomes, including improved forecasting, customer relations, and corporate sustainability.[18] It is also considered a central element in knowledge management that fosters innovation.[19,20] However, findings on its link with innovation are mixed. While Darroch[17] found no significant connection between KD and Green Innovation (GI) in New Zealand firms, other studies in Taiwan and China highlight strong positive relationships.[21]

Social capital theory emphasizes the importance of interpersonal ties and networks in facilitating knowledge sharing, which is essential for adopting sustainable technologies and eco-friendly practices. While open knowledge exchange fosters green innovation, methodological challenges remain. In SEM models, endogeneity may arise when innovation-oriented culture simultaneously drives knowledge dissemination (KD) and innovation outcomes, while KD may also influence innovation indirectly through knowledge application. Drawing upon the existing literature and theoretical frameworks, the following hypothesis is proposed:

H1b: ***Knowledge dissemination has a positive impact on innovations in green products and processes.***

Knowledge Application

Knowledge Application (KAP) refers to an organization's ability to effectively utilize acquired knowledge to solve problems, support decision-making, and improve products, services, and internal operations. Knowledge Application enhances the relevance and utility of knowledge, allowing organizations to respond strategically to customer needs and dynamic market conditions.[16,2] It plays a critical role in translating insights into concrete innovation initiatives, particularly in product development. Moreover, KAP enables the transformation of internal capabilities into tangible product and process innovations.[22] From a sustainability perspective, applying knowledge facilitates the development of environmentally responsible products and the adoption of cleaner production technologies.[23]

The dynamic capabilities framework underscores KAP as a core mechanism for converting organizational knowledge into innovation outcomes. Without application, knowledge remains latent and fails to generate value. However, methodological challenges must be considered. In structural models, the influence of KAP may be mediated by preceding KM activities such as acquisition and dissemination. Additionally, feedback loops may occur, where knowledge application stimulates new learning and further knowledge-seeking behavior.

Grounded in theory and empirical findings, the following hypothesis is proposed:

H1c: ***Knowledge application has a positive impact on innovations in green products and processes.***

Hypotheses H1a–H1c examine how different dimensions of knowledge management affect green product and process innovations (GPPI). In the model, GPPI mediates the relationship between knowledge constructs and organizational outcomes, including environmental performance (ENVP), economic performance (ECOP), and management commitment to ecology (MCE). Indirect effects (e.g., KA → GPPI → ENVP) will be tested using bootstrapping in PLS-SEM, indicating whether KM influences performance primarily through innovation. Potential endogeneity—due to omitted variables, reverse causality, or measurement error—will be addressed through control variables and robustness checks to enhance validity.

The Impact of Green Product and Process Innovations on Sustainable Development

Sustainable Performance

Green Product and Process Innovations (GPPI) involve the development of environmentally friendly products and the adoption of sustainable production technologies aimed at minimizing environmental harm while improving resource efficiency and operational performance. In response to growing environmental concerns and the depletion of natural resources, organizations are increasingly turning to green innovations to enhance sustainability and maintain competitiveness.[20] Although the concept of sustainable performance remains multidimensional and contested, according to Hahn *et al.*[24], its relevance continues to grow, especially for Small and Medium-sized Enterprises (SMEs) seeking to meet regulatory, ethical, and market expectations.[19] Through initiatives such as energy-efficient operations, recycling, and eco-conscious product design, GPPI plays a pivotal role in reducing emissions, conserving resources, and enhancing organizational adaptability.[3]

The Triple Bottom Line (TBL) framework, according to Elkington[25], emphasizes environmental, economic, and social sustainability, while stakeholder theory underscores aligning innovation with stakeholder values. Within these perspectives, green product and process innovations (GPPIs) serve not only for environmental compliance but also as strategic assets that create long-term value and social legitimacy. GPPIs advance sustainable development by delivering ecological benefits - such as waste reduction and cleaner production - and competitive advantages, including cost savings, enhanced reputation, and access to new markets.

Based on these arguments and prior research, the following hypothesis is proposed:

H2: ***Innovations in green products and processes positively influence the sustainable development of organizations.***

Environmental performance

Environmental Performance (ENVP) reflects an organization's capacity to minimize its ecological footprint through pollution control, resource conservation, waste management, and adoption of clean, efficient technologies. Achieving environmental sustainability demands transformative changes in production technologies, with clean technologies acting as a primary driver of Green Product and Process Innovations (GPPI) that meet rising environmental and market expectations.[26] Organizations prioritizing resource efficiency and environmental stewardship are better positioned to reduce environmental degradation while fulfilling strategic goals and stakeholder demands.[4] Empirical studies confirm that firms with strong environmental management orientations tend to integrate GPPI within their strategies, enhancing both sustainability and operational performance.[27] Furthermore, GPPI fosters competitiveness, demonstrating that eco-conscious innovations can simultaneously drive market success.[28]

The Ecological modernization theory provides a valuable framework for understanding this relationship, positing that technological advancements - especially green innovations - can realign industrial production with environmental preservation and economic development. This theory supports a direct positive impact of GPPI on environmental sustainability. However, indirect effects, such as mediation by knowledge management processes and potential endogeneity issues, must also be considered (e.g., firms with superior environmental performance may be more inclined to invest in GPPI).

H2a: *Green product and process innovations significantly influence the sustainability of environmental performance.*

Social Sustainability

Social Sustainability (SOCS) refers to an organization's dedication to social and ecological values, encompassing employee well-being, equity, workplace safety, internal education, and community engagement. It includes initiatives aimed at human development, communication enhancement, equitable employment, and health and safety promotion. From a strategic standpoint, internal capacity-building and organizational development are essential for green innovation.[23] Mechanisms such as absorptive capacity and relationship learning support firms in integrating external knowledge to drive sustainability outcomes, aligning with the United Nations Sustainable Development Goals (SDGs). Studies across diverse sectors highlight that sustainable development is best achieved through the integration of various strategic frameworks, including green innovation, Corporate Social Responsibility (CSR), Total Quality Management (TQM), and absorptive capacity.[29]

Green product and process innovations can shift managerial focus toward deeper commitments to social and environmental responsibilities. By institutionalizing sustainability values, GPPI may shape organizational culture and behaviors in a normative way. However, this relationship might be reciprocal, as firms with established social commitments may also be more likely to adopt GPPI, introducing the potential for reverse causality.

H2b: *Green product and process innovations positively influence management's commitment to ecological and social sustainability.*

The Mediating Impact of Knowledge Management on Sustainable Performance

Sustainable Development (SD) involves the integration and achievement of environmental, economic, and social sustainability through long-term strategic planning and responsible business practices. Existing research identifies Knowledge Management (KM) as a key strategic driver for enhancing organizational innovation performance.[16] Specifically, a growing body of literature supports a direct positive relationship between KM processes and the advancement of Green Product and Process Innovations (GPPI), which in turn contribute significantly to sustainable development outcomes.[19,29] Different types of innovation require tailored resources and distinct KM strategies, suggesting that the alignment of KM activities - such as knowledge acquisition, dissemination, and application—with innovation objectives is essential for achieving long-term sustainability.[16]

Grounded in the Resource-Based View (RBV), knowledge is viewed as a core intangible asset enabling firms to build capabilities that generate measurable ecological, economic, and social value. It is also plausible that KM's impact on sustainable development is partially mediated by GPPI, which acts as an operational mechanism translating knowledge into concrete sustainability outcomes.

H3: *The knowledge management process has a positive impact on sustainable development.*

Advanced Technologies and the Mediating Role of Knowledge Management

Mediation refers to an indirect effect where one variable influences another through an intermediary mechanism. In this context, KM may mediate the relationship between GPPI and sustainable development. Prior studies highlight that mediation is particularly important when organizational leadership supports green innovation by leveraging employee knowledge and capabilities.[30] Green product and process innovations drive corporate sustainability by enhancing flexibility and performance through advanced technologies and effective KM practices.[31,27] Digital transformation (AI, ML, IoT) can optimize production and reduce energy use by 10–15%.[32] Smart waste management improves recycling efficiency and lowers emissions, according to Czekala *et al.*[33], while waste-to-energy and nanotechnologies further support the circular economy and pollution control.[34] These developments underscore the need for robust knowledge capabilities, with KM acting as a transformative mechanism to absorb, manage, and apply green innovations, generating measurable sustainability outcomes.[35]

Thus, the relationship between GPPI and SD is complex and multilayered, with KM acting as a key mediator embedding sustainability into organizational practices. Structural Equation Modeling (SEM) is well-suited to test such complex indirect and multiple mediation effects.

H4: *Knowledge management mediates the relationship between green product and process innovations and sustainable development.*

Conceptual Model Overview

The conceptual model emerging from these hypotheses positions KM dimensions (KA, KD, KAP) as antecedents to GPPI, which in turn affect sustainable development outcomes: Environmental Performance (ENVP), Economic Performance (ECOP), and Management Commitment to Ecology (MCE). Knowledge Management is also hypothesized to exert a direct and indirect influence on SD via innovation. This model will be empirically tested using the PLS-SEM approach in the subsequent section. Based on the previously reviewed literature, a proposed conceptual model is presented (Fig. 1):

Methodological Aspects of the Research

Statistical Data Processing Methods

The empirical study applied a structured methodology using questionnaires to collect data from manufacturing and service organizations in Serbia registered with the Business Registers Agency (APR) and holding ISO certifications. A non-probability sample of 300 organizations of varying sizes and types was surveyed. Descriptive statistics were used to analyze item characteristics and respondent profiles, employing IBM SPSS v.17. The measurement model was tested for convergent validity, internal consistency, and discriminant validity.[36] Structural relationships among latent constructs were assessed using Partial Least Squares SEM (PLS-SEM) via Smart PLS v.4, evaluating the significance of paths and overall model fit.

Analysis and Evaluation of the Measurement Model

When developing a measurement model, it is essential to consider that there are two broad types of measurement specification: reflective and formative measurement models. Additionally, the measurement model examines the relationship between constructs and indicators based on measurement theory. The Partial Least Squares SEM method was chosen as the appropriate methodological approach due to the exploratory nature of the research model, which aims to predict and explain the relationships between knowledge management, green innovation, and sustainable performance. This method is particularly suitable for:

- Complex models with multiple latent constructs and indicators,
- Small to medium sample sizes (n = 300),
- Data that do not follow a normal distribution,

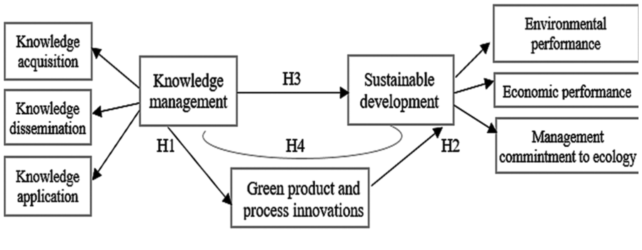

Fig. 1 — Research model

- Both formative and reflective indicators,
- Studies focused on maximizing the explained variance (R^2).

Unlike CB-SEM, which is typically used for testing well-established theoretical models, PLS-SEM enables the testing and development of new theoretical frameworks. It has therefore proven to be a methodologically appropriate choice for this study. This study applies a reflective measurement model, where indicators mirror underlying constructs and are expected to be highly correlated.[36] In such models, the removal of single indicators does not affect the construct's meaning if reliability is preserved. The measurement model was assessed through Confirmatory Factor Analysis (CFA), examining knowledge acquisition, sharing, and application in fostering green product and process innovations, along with managerial commitment to ecology. Reliability and convergent validity were tested using outer loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). Most outer loadings exceeded 0.70, confirming convergent validity, with exceptions (KA4 = 0.457, MCE1 = 0.491, MCE7 = 0.658) retained for theoretical reasons. All constructs showed satisfactory internal consistency, with CR ranging from 0.859 (KA) to 0.941 (GPPI), and AVE values above 0.50.

Cross-loadings indicate correlations between items and all latent constructs. Each item should load highest on its intended construct, with the primary loading ≥ 0.70 (≥ 0.60 in early model development) and at least 0.10 higher than cross-loadings. Items are retained if they load ≥ 0.70 on the target construct, show no problematic cross-loadings, and their removal does not improve reliability or validity; theoretical justification may also support retention. Loadings of 0.40–0.70 may be acceptable if they enhance model fit, while items below 0.40 are usually removed.

Through confirmatory factor analysis, internal consistency and convergent validity were assessed. Cronbach's coefficient (α) was used to evaluate internal consistency.[37] Cronbach's alpha for the full sample is 0.761, with group-specific values shown in Table 2. Values ≥0.70 are generally considered acceptable, indicating satisfactory internal consistency.[38] The ρA (rhoA) coefficient, derived from CFA factor loadings, provides an improved measure of internal consistency over Cronbach's alpha, with values above 0.70 indicating acceptable reliability.[39] In this study, rhoA values ranged from 0.857 to 0.935, demonstrating high reliability (Table 3). Convergent validity was confirmed, with AVE ≥ 0.50 and all factor loadings statistically significant ($p < 0.10$, $p < 0.05$). Construct reliability and validity are summarized in Table 3.

Model Evaluation

The validity of the measurement model was assessed by examining the reliability, as well as the convergent and discriminant validity of all reflective constructs. The research model and hypotheses from the perspective of structural modeling are shown in Fig. 2.

Table 2 — Demographic statistics of the sample

Variable	Option	Number	Percentage (%)
Company type	1 – Processing industry	77	25.7
	2 – Services	151	50.3
	3 – Others	72	24.0
Company status	1 – Public	26	8.7
	2 – Private	272	90.7
	3 – Mixed	2	0.7
Number of employees	≤10	213	71.0
	11–50	28	9.3
	51–250	39	13.0
	>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	34.0
	Postgraduate	67	22.3
Age	≤29	33	11
	30–44	151	50.3
	45–54	108	36.0
	≥55	8	2.7
Gender	Male	213	71.0
	Female	87	29.0
Years of work experience	≤5	43	14.3
	6–15	142	47.3
	16–25	100	33.3
	≥26	15	5.0

Table 3 — Confirmatory factor analysis results (CFA)

	Cronbach's alpha (α)	rhoA	Composite reliability (CR)	Average variance extracted (AVE)
KA	0.813	0.905	0.859	0.557
KD	0.886	0.891	0.913	0.638
KAP	0.864	0.869	0.902	0.650
GPPI	0.927	0.936	0.941	0.695
ENVP	0.924	0.935	0.940	0.724
ECOP	0.852	0.857	0.890	0.575
MCE	0.865	0.871	0.896	0.524

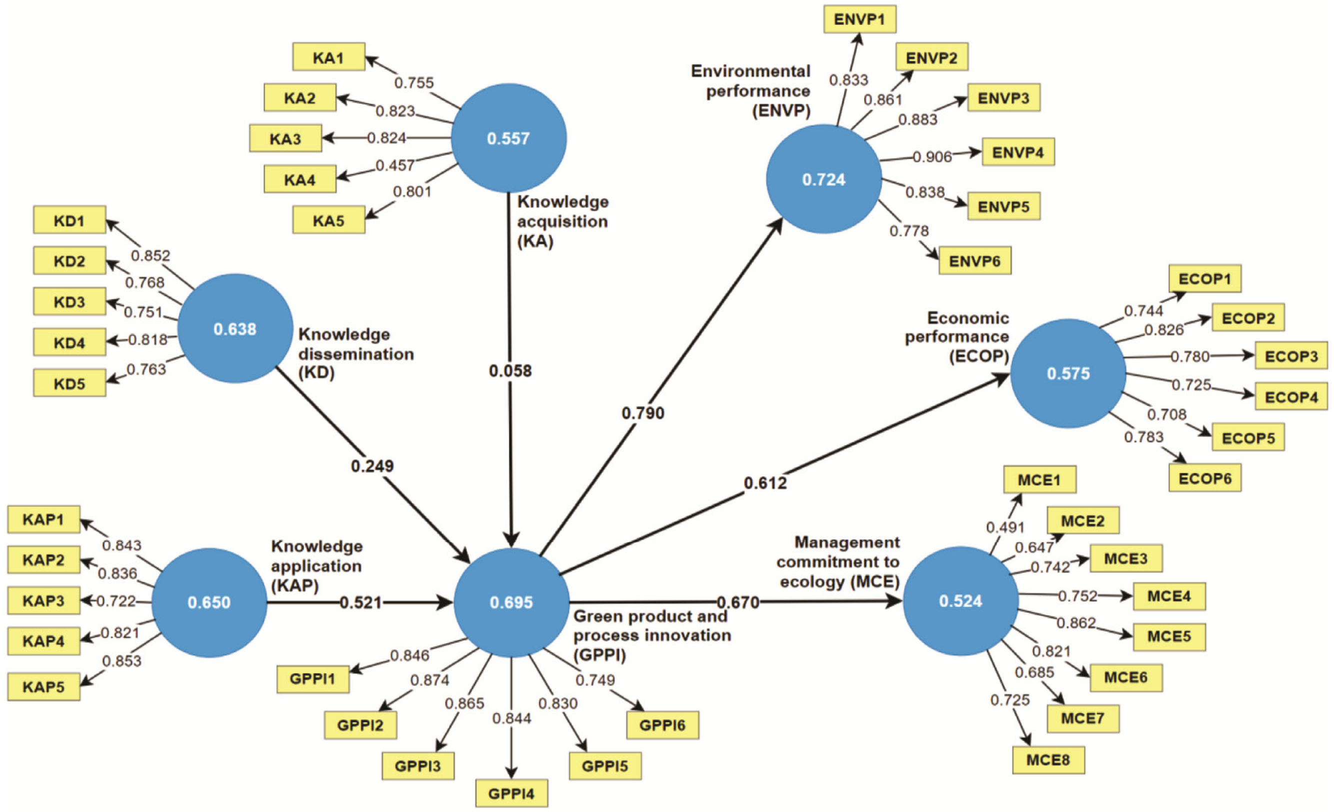

Fig. 2 — Structural model in the software Smart PLS

Convergent Validity

Convergent validity reflects the degree to which items of a construct are correlated, implying that reflective indicators should share substantial variance.[34] It is assessed through outer loadings, Cronbach's Alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE). Outer loadings should exceed 0.708, meaning each indicator shares at least 50% of its variance with the latent construct. Similarly, an AVE of 0.50 or higher indicates that the construct explains more than half of the variance of its indicators. In this study, all AVE values are above 0.50 (Table 3), confirming convergent validity. Reliability, measured by Cronbach's Alpha and CR, also ranges between 0 and 1, with higher values denoting stronger internal consistency (Table 4).

Based on the displayed values, Cronbach's Alpha ranged from 0.813 to 0.927, while CR values ranged from 0.859 to 0.941. Both indicators have statistical reliability exceeding the required threshold of 0.70. Thus, considering CR, all values are between 0.70 and 0.90 and can be considered satisfactory. Based on the values of Cronbach's Alpha and CR, a satisfactory level of internal consistency of reflective indicators was confirmed.

Discriminant Validity

Discriminant validity exists when AVE is greater than the shared variance with all other constructs. Covariance-based SEM usually relies on the Fornell-Larcker method, while PLS-SEM recommends the Heterotrait-Monotrait (HTMT) correlation method. The removal of weak items KA4 and MCE1 enhanced construct reliability and validity. For Knowledge Acquisition (KA), Cronbach's Alpha improved from 0.741 to 0.919, CR from 0.812 to 0.859, and AVE from 0.593 to 0.689, indicating substantial gains in reliability and convergent validity. For Management Commitment to Ecology (MCE), removing MCE1 raised Cronbach's Alpha from 0.612 to 0.689, CR from 0.802 to 0.823, and AVE from 0.525 to 0.574, reflecting only modest improvement, still below the α ≥ 0.70 threshold. Thus, excluding KA4 is clearly justified, while MCE1 may also be removed, though weaker items (e.g., MCE2, loading = 0.649) warrant further consideration. Discriminant validity was assessed using the Fornell–Larcker criterion,

Table 4 — Reliability and convergent validity of model factors

Construct	Item	Outer loadings	A	CR	Construct	Item	Outer loadings	A	CR
Knowledge acquisition (KA)	KA1	0.755	0.813	0.859	Environmental performance (ENVP)	ENVP1	0.833	0.924	0.940
	KA2	0.823				ENVP2	0.861		
	KA3	0,824				ENVP3	0.883		
	KA4	0.457*				ENVP4	0.906		
	KA5	0.801				ENVP5	0.838		
Knowledge dissemination (KD)	KD1	0.852	0.886	0.913		ENVP6	0.778		
	KD2	0.768			Economic performance (ECOP)	ECOP1	0.744	0.852	0.890
	KD3	0.751				ECOP2	0.826		
	KD4	0.818				ECOP3	0.780		
	KD5	0.763				ECOP4	0.725		
Knowledge application (KAP)	KAP1	0.843	0.866	0.902		ECOP5	0.708		
	KAP2	0.836				ECOP6	0.783		
	KAP3	0.722			Management commitment to ecology (MCE)	MCE1	0.491*		
	KAP4	0.821				MCE2	0.647*		
	KAP5	0.853				MCE3	0.742		
Green product and process innovation (GPPI)	GPPI1	0.846	0.927	0.941		MCE4	0.752	0.865	0.896
	GPPI2	0.874				MCE5	0.862		
	GPPI3	0.865				MCE6	0.821		
	GPPI4	0.844				MCE7	0.685*		
	GPPI5	0.830				MCE8	0.725		
	GPPI6	0.749							

Table 5 — Fornell – Larcker Matrix

Constructs	KA	KD	KAP	GPPI	ENVP	ECOP	MCE
KA	0.746	0.401	0.518	0.428	0.319	0.471	0.499
KD	0.401	0.798	0.777	0.678	0.732	0.623	0.532
KAP	0.518	0.777	0.806	0.745	0.630	0.526	0.686
GPPI	0.428	0.678	0.745	0.833	0.790	0.612	0.670
ENVP	0.319	0.732	0.630	0.790	0.851	0.665	0.579
ECOP	0.471	0.623	0.526	0.612	0.665	0.758	0.450
MCE	0.499	0.532	0.686	0.670	0.579	0.450	0.724

confirming that the square roots of AVE exceeded inter-construct correlations (Table 5).

To assess the discriminant validity of the model, the Fornell–Larcker criterion was applied. This criterion requires that the square roots of the AVE values (√AVE) exceed the inter-construct correlations among latent variables. The results are as follows:

- The √AVE for *Knowledge Acquisition (KA)* is 0.746, which is higher than all correlations between KA and other constructs (e.g., 0.518 with KAP, 0.428 with GPPI).
- The √AVE for *Knowledge Dissemination (KD)* is 0.798, which also exceeds all of its correlations with other constructs (e.g., 0.777 with KAP).
- The √AVE values for all other constructs (KAP, GPPI, ENVP, ECOP, MCE) likewise surpass all corresponding inter-construct correlations.

Thus, discriminant validity is confirmed - each construct is sufficiently distinct from the others. The heterotrait-monotrait correlation method is the correlation ratio between traits and correlations within traits, meaning that the HTMT criterion assumes a true correlation between two constructs if they were ideally measured, i.e., ideally reliable.[34] The proposed threshold level for the HTMT criterion is 0.85 and 0.90 for conceptually similar constructs.[34] If the correlation between two constructs approaches 1, it indicates a lack of discriminant validity. However, none of the construct pairs exceed the liberal threshold level (0.90), confirming the discriminant validity of the constructs based on the results obtained (see Table 6).

Table 6 — HTMT values

	KD	EVNP	ECOP	GPPI	MCE	KAP	KA
KD	1						
EVNP	0.732	1					
ECOP	0.623	0.665	1				
GPPI	0.678	0.790	0.612	1			
MCE	0.532	0.579	0.450	0.670	1		
KAP	0.777	0.630	0.526	0.745	0.686	1	
KA	0.401	0.319	0.471	0.428	0.499	0.518	1

In addition, all HTMT values are below the recommended thresholds (0.85 or 0.90 for conceptually similar constructs):

- The highest HTMT value is 0.790 between GPPI and ENVP, which falls within the acceptable range.
- All other values are significantly lower, further confirming the absence of overlap among the constructs.

In summary, the model meets the criteria for discriminant validity according to both the Fornell–Larcker and HTMT approaches. With this step, the model evaluation was successfully completed; all assessment criteria were met.

Structural Model Analysis

Structural Equation Modeling (SEM) was applied using Partial Least Squares (PLS-SEM) with Smart PLS v.4.1.0.2 to assess relationships among latent variables. Path coefficients (β) and coefficients of determination (R^2) were calculated, with significance tested through non-parametric bootstrapping, which evaluates estimates such as path coefficients, Cronbach's alpha, HTMT, and R^2.Results show that knowledge dissemination (KD) and knowledge application (KAP) significantly influence GPPI (β = 0.249 and 0.521, $p < 0.001$). GPPI further demonstrates strong positive effects on environmental performance (ENVP, β = 0.790), economic performance (ECOP, β = 0.612), and management commitment to ecology (MCE, β = 0.670). These findings confirm hypotheses H1, H2, and H3 (see Table 7).

While gathering additional evidence for hypotheses H1, H2, and H3, the indirect relationship between KM and ENVP, ECOP, and MCE was examined, revealing positive regression coefficients (which are statistically significant at $p < 0.001$), indicating the influence of KD and KAP on ENVP, ECOP, and MCE, and thereby supporting H2 and H3 (see Table 8). However, regarding the influence of Knowledge Acquisition (KA) on ENVP, ECOP, and MCE, the regression coefficients are significantly low (which are not statistically significant at $p > 0.05$), leading to the conclusion that hypothesis H1a is not confirmed.

The effects of Knowledge Acquisition (KA), Dissemination (KD), and Application (KAP) were tested. KA showed positive but insignificant effects on Environmental Performance (ENVP), Economic Performance (ECOP), and Management Commitment to Ecology (MCE), leading to the rejection of H1a, likely due to reliance on standard sources and limited training. Indirectly, KA exerted only minor influence through GPPI, whereas KAP strongly affected ENVP (41.2%), ECOP (31.9%), and MCE (34.9%). The coefficient of determinationR^2 values (0.524–0.724) indicate moderate to high predictive accuracy.[40] KD and KAP explained 65% and 63.8% of GPPI variance, while ENVP explained 72.4% of KM variance, underscoring GPPI's mediating role in linking KM to sustainable performance (Table 9).

Similar results support the assertions of various authors, advocating for a more intensive approach to

Table 7 — Path coefficients

Path coefficient	Standardized regression coefficient (β)	Sample mean (MEAN)	Standard deviation (STDEV)	t – values (0/STDEV)	p – values
KD → GPPI	0.249	0.250	0.048	5.232	0.000
KAP → GPPI	0.521	0.520	0.056	9.337	0.000
GPPI → ENVP	0.790	0.790	0.020	38.676	0.000
GPPI → ECOP	0.612	0.613	0.039	158.12	0.000
GPPI →MCE	0.670	0.672	0.027	24.948	0.000
KA → GPPI	0.058	0.061	0.031	1.866	0.062

Table 8 — Total indirect effects of KM on SD

Path coefficient	Standardized regression coefficient (β)	Sample mean (MEAN)	Standard deviation (STDEV)	t – values (0/STDEV)	p – values
KD →ENVP	0.197	0.197	0.039	5.071	0.000
KD → ECOP	0.153	0.153	0.033	4.694	0.000
KD → MCE	0.167	0.168	0.033	5.119	0.000
KAP → ENVP	0.412	0.411	0.044	9.422	0.000
KAP → ECOP	0.319	0.318	0.035	9.108	0.000
KAP → MCE	0.349	0.349	0.041	8.595	0.000
KA → ENVP	0.045	0.048	0.025	1.855	0.064
KA → ECOP	0.035	0.037	0.019	1.828	0.068
KA → MCE	0.039	0.041	0.021	1.859	0.063

*significance level of p<0,001

knowledge acquisition. This involves restructuring interventions in fiscal policy, which should be adaptable and, in cases of insufficient maneuvering space, amending the structure of public revenues and expenditures. Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio, with all values falling below the 0.90 threshold, indicating that the constructs are empirically distinct.[39] To assess the contribution of each exogenous construct to the R^2 value of an endogenous construct, the effect size f^2 was calculated using the following formula, as implemented in Smart PLS:

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

where, R^2 included - R^2 value of the endogenous construct when the predictor is included in the model, R^2 excluded - R^2 value when the predictor is excluded. This coefficient reflects the change in explained variance due to the inclusion of a specific exogenous construct. According to Cohen & Levinthal[41] guidelines: **s**mall effect: $f^2 \geq 0{,}02$, medium effect: $f^2 \geq 0{,}15$, large effect: $f^2 \geq 0{,}35$. Effect size values below 0.02 suggest a negligible impact of the exogenous variable on the endogenous construct. To illustrate, consider the effect of *KA* on *GPPI*. When KA is included in the model, the R^2 value for GPPI is 0.695. When KA is excluded, the R^2 drops to 0.688. Applying the formula:

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}} = \frac{0.695 - 0.688}{1 - 0.695} = \frac{0.007}{0.305} \approx 0.023$$

The structural model results presented in Table 10 provide insights into the strength and magnitude of the relationships between key constructs. The f^2 values for the remaining endogenous constructs are presented in Table 10.

The effect of Knowledge Acquisition (KA) on GPPI is weak (β = 0.058, f^2 = 0.023), while Knowledge Dissemination (KD) exerts a moderate impact (β = 0.249, f^2 = 0.420) and Knowledge Application (KAP) shows the strongest influence (β = 0.521, f^2 = 1.836). GPPI strongly predicts sustainability outcomes — ENVP (β = 0.790, f^2 = 2.623), ECOP (β = 0.612, f^2 = 1.353), and MCE (β = 0.670, f^2 = 1.101) — confirming its mediating role between KM and performance, with KAP as the dominant driver of green innovation. The weak KA effect highlights deficiencies in knowledge sourcing strategies. Common Method Bias was assessed via Harman's test; the first factor explained 38.67% of variance, below the 50% threshold, indicating no major concern, though confirmatory approaches (e.g., CLF in CFA) are preferable for robustness (Table 11).

Table 9 — Indirect effects and values of the coefficient of determination for latent constructs in the structural model

Indirect effects		Coefficient of determination	
Path coefficients (β)	Specific indirect effects	Construct	R^2
KA – GPPI – ENVP	0.046	KA	0.557
KA – GPPI – ECOP	0.036	KD	0.638
KA – GPPI – MCE	0.039	KAP	0.650
KD – GPPI – ENVP	0.046	GPPI	0.695
KD – GPPI – ECOP	0.153	ENVP	0.724
KD – GPPI – MCE	0.167	ECOP	0.575
KAP – GPPI – ENVP	0.412	MCE	0.524
KAP – GPPI – ECOP	0.319	KA	0.557
KAP – GPPI – MCE	0.349	—	—

Table 10 — Effect size (f^2) calculation

Endogenous construct	β	R^2	f^2	Effect size
KA → GPPI	0.058	0.695	0.023	Small
KD → GPPI	0.249	0.695	0.420	Large
KAP → GPPI	0.521	0.695	1.836	Very large
GPPI → ENVP	0.790	0.724	2.623	Very large
GPPI → ECOP	0.612	0.575	1.353	Very large
GPPI → MCE	0.670	0.524	1.101	Very large

Table 11 — Total variance explained

	Initial Eigen values			Extraction sums of squared loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	20.495	38.669	38.669	20.495	38.669	38.669
2	4.888	9.222	47.891			
3	3.793	7.157	55.048			
4	3.149	5.942	60.989			
5	2.652	5.004	65.993			
6	2.012	3.795	69.789			
7	1.866	3.520	73.309			
8	1.710	3.226	76.535			

Predictive relevance was assessed using the Stone-Geisser Q^2 coefficient via the blindfolding procedure. Although Q^2 values are not explicitly presented in Table 12, the high R^2 values suggest strong predictive relevance.

To identify mediation effects, the Variance Accounted for (VAF) values were calculated using the following formula:

$$VAF = \frac{Indirect\ effect}{Overall\ effect} = \frac{a \cdot b}{a \cdot b + c}$$

where, a - the path coefficient between the independent variable and the mediator, b - the path coefficient between the mediator and the dependent variable, c - the direct path coefficient between the independent and the dependent variable (see Fig. 2). According to Hair *et al.*[36], the following thresholds are accepted: VAF < 20% → no mediation, 20% ≤ VAF ≤ 80% → partial mediation, VAF > 80%→ full mediation. The VAF values exceeded 80% in all cases, which indicates *full mediation*. From the model diagram, VAF can be calculated for the following cases:

1. KAP → GPPI → ENVP
a = KAP → GPPI = 0.521
b = GPPI → ENVP = 0.790
c = KAP → ENVP = 0 (no direct relationship)

$$VAF = \frac{a \cdot b}{a \cdot b + c} = \frac{0{,}521 \cdot 0.790}{0.521 \cdot 0.790 + 0} = \frac{0.41159}{0.41159} = 1.000$$

Thus, the effect is fully mediated, indicating a 100% indirect effect. The calculated VAF values for the other indirect effects are presented in Table 13.

Path KAP and ENVP, KAP and ECOP, and KAP and MCE, as the direct effects (c) were not significant (i.e., c = 0), while the indirect effects were significant. To evaluate the contribution of independent variables in explaining the dependent variables, effect size coefficients (f^2) were calculated.

Table 12 — Blindfolding procedure

Construct	R^2	Assumed Q^2	Interpretation
GPPI	0.695	$Q^2 > 0.35$	High relevance
ENVP	0.724	$Q^2 > 0.35$	High relevance
ECOP	0.575	$Q^2 \approx 0.30$	Moderate–high
MCE	0.524	$Q^2 \approx 0.30$	Moderate–high

Table 13 — VAF Values

Path	VAF	Type of Mediation
KAP → GPPI → ENVP	1.000	Full mediation
KA → GPPI → ENVP	1.000	Full mediation
KD → GPPI → ENVP	1.000	Full mediation
GPPI → MCE → ECOP	≈ 0.401	Partial mediation

Results and Discussion

Findings show that Knowledge Dissemination (KD) and Knowledge Application (KAP) significantly enhance Green Product and Process Innovations (GPPI) (β = 0.240; β = 0.521), with KD strengthening employee capabilities and innovation potential. GPPI strongly influences Sustainable Performance (SP)—Environmental (β = 0.790), Economic (β = 0.612), and Managerial Commitment to Ecology (β = 0.670)—and partially mediates the KM–SP link. Structural model assessment in Smart PLS confirmed measurement reliability, validity, and theoretical alignment. Overall, KM is a strategic driver of sustainability-oriented innovation, though its impact in transitional economies such as Serbia remains constrained by systemic and institutional barriers.

This study highlights the complex, context-dependent link between knowledge management (KM) and green product and process innovation (GPPI), particularly in transitional economies such as Serbia. While KM is a strategic enabler of sustainability-oriented innovation, its effectiveness is limited by systemic, institutional, and organizational constraints. Absorptive capacity theory suggests that Serbian firms often lack the structures to identify, assimilate, and apply external knowledge, especially for systemic eco-innovation, which is compounded by low R&D investment, weak university–industry collaboration, and scarce policy incentives.[43] The Resource-Based View (RBV) emphasizes misalignment between KM and innovation objectives in resource-constrained environments, according to Teece *et al.*[6], while the Dynamic Capabilities Framework highlights the need for adaptive reconfiguration of resources, which is often limited in reactive firms.[42]

Systemic capacity building is needed, including stronger policies, enhanced university–industry collaboration, and integration of KM into national sustainability agendas. Comparative evidence shows that EU firms leverage policy-aligned, digitally integrated KM for systemic innovation, according to Del Giudice *et al.*[43],whereas Southeast Asian firms adopt adaptive, incremental approaches supported by technology-enabled networks and training, according to Le P B & Tran K T[44], illustrating how institutional maturity shapes KM and green innovation outcomes. Feedback loops between KM and GPPI further reinforce iterative learning, as empirically validated in longitudinal studies.[45] Overall, successful KM implementation depends on organizational readiness and alignment with broader sustainability policies.

Practical Implications

This study offers actionable insights for manufacturing managers and decision-makers pursuing eco-innovation while balancing environmental, economic, and social objectives. It highlights the strategic role of Knowledge Management (KM)—including acquisition, dissemination, and application—as a key driver of Green Product and Process Innovations (GPPIs) and sustainable performance. A key managerial implication is strengthening Management Commitment to Ecology (MCE) to enhance long-term competitiveness under environmental uncertainty. While findings are most relevant for certified firms adhering to formal environmental standards, they also indicate the need to examine KM's role in uncertified SMEs, where resource constraints may limit structured innovation systems.

For *micro-enterprises*, simple KM tools - such as shared digital repositories, community workshops, and peer-to-peer learning - can enhance eco-innovation capacities, particularly when supported by institutional mechanisms like grants and tax incentives. Large enterprises are advised to integrate formal KM systems with ERP and CRM platforms, foster transformational leadership, and establish internal knowledge hubs, cross-functional teams, and collaborations with academia and green startups to drive system-level sustainability outcomes.

Methodologically, the cross-sectional design limits causal inference; future studies should adopt multi-wave longitudinal designs or Latent Growth Modeling (LGM) to track KM evolution and its impact on GPPI, mitigating common method bias.

Future research should also examine moderators such as leadership style (transformational vs. transactional) and institutional readiness, while controlling for firm size, industry, and location. The proposed framework positions KM as the independent variable, GPPI as the outcome, and encourages latent variable modeling to validate direct and interaction effects, enhancing generalizability across industries and regions.

Conclusions

This study explored how Knowledge Management (KM) processes enhance Green Product and Process Innovation (GPPI) and, in turn, contribute to Sustainability Performance (SP) in manufacturing firms. Results confirmed that knowledge development and knowledge acquisition practices significantly influence GPPI, supporting previous empirical findings. Furthermore, GPPI demonstrated a strong positive impact on all dimensions of SP, including environmental, economic, and managerial commitment to sustainability. Mediation analysis revealed that GPPI partially mediates the relationship between KM and SP. The Smart PLS analysis confirmed good model validity, reliability, and predictive power. Discriminant validity was established through both the Fornell–Larcker criterion and the HTMT ratio, confirming the constructs as empirically distinct. Although the sample included a large share of micro firms and senior-level respondents, which may introduce bias, the model's robustness remains strong. Overall, this study provides empirical evidence that KM significantly supports green innovation, which in turn enhances sustainability performance, and highlights the strategic value of KM in competitive, sustainability-oriented manufacturing contexts.

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