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Enablers for green lean six sigma adoption in the manufacturing industry

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Abstract

Purpose – The objective of this article is to identify the relationships between the enablers in the implementation of Green Lean Six Sigma (GLSS) in the Mexican manufacturing industry (MMI).

Design/methodology/approach – To create the survey instrument, the authors did an extensive literature research, which they then applied in the MMI to find the relationships between enablers and their impact on the positive effects of implementing GLSS projects. Using exploratory and confirmatory factor analyses (EFA and CFA), the data were empirically and statistically corroborated. Furthermore, the authors validated the hypotheses that support the research using the structural equation modeling (SEM) approach in SPSS Amos.

Findings – The findings reveal that leadership has a positive impact on social and economic benefits (EcB), as well as an indirect impact on the environmental benefits (EB) of GLSS projects, with organizational involvement (OI) and performance measurement (PM) functioning as mediators.

Practical implications – This study represents an empirical reference for practitioners and researchers pursuing high-quality, low-cost, environmentally and socially sustainable products or processes through the implementation of GLSS projects in the manufacturing industry.

Originality/value – This study provides a statistically validated model using the SEM technique to represent the relationships between GLSS enablers in the MMI.

Keywords Green manufacturing, Critical success factors, Enablers, Lean six sigma, Manufacturing industry, Structural equation modeling

Paper type Research paper

Abbreviations

LM	Lean Manufacturing
SS	Six Sigma
LSS	Lean Six Sigma
LG	Lean Green
GLSS	Green Lean Six Sigma
LDR	Leadership
OI	Organizational Involvement
PM	Performance Measurement
EcB	Economic Benefits
EB	Environmental Benefits
SB	Social Benefits

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VIF	Variance Inflation Factors
EFA	Exploratory Factor Analysis
CFA	Confirmatory Factor Analysis
SEM	Structural Equation Modeling
CSFs	Critical Success Factors
KMO	Kaiser–Meyer–Olkin index
MMI	Mexican Manufacturing Industry
AMM	World Medical Association
KMO	Kaiser–Meyer–Olkin index
CMIN/DF	Minimum Discrepancy Coefficient/Degrees of Freedom
PNFI	Parsimony Norm Fit index
CFI	Comparative Fit Index
TLI	Tucker–Lewis Index
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Residual
AVE	Average Variance Extracted
SRW	Standardized Regression Coefficients
CR	Critical Coefficient
P	Probability value

Quick value overview

Interesting because - This article explores the enablers for adopting Green Lean Six Sigma (GLSS) in the manufacturing industry, focusing on integrating sustainability and efficiency. Using factor analysis and structural equation modeling (SEM), it identifies how these enablers impact the economic benefits (EcB), social benefits (SB) and environmental benefits (EB) of GLSS projects. The study is distinguished by providing a statistically validated model to represent the relationships between GLSS facilitators, something little explored in previous research. It demonstrates that GLSS implementation can simultaneously enhance operational efficiency and sustainability, offering new empirical evidence for the manufacturing sector.

Theoretical value - The study contributes theoretically by explaining how the effective combination of Lean, Green and Six Sigma (SS) practices can optimize production processes from a cost and efficiency perspective, also incorporating environmental and social performance aspects. Furthermore, the findings reported here provide valuable information that helps clarify the mechanisms through which adequate leadership (LDR), organizational participation and performance measurement (PM) interact in this integrated approach to support sustainability in manufacturing.

Practical value- This study is vital for managers, showing that adopting GLSS enhances sustainability and efficiency, yielding significant returns on investment across social, economic and environmental dimensions. The validated causal relationships between facilitators motivate managers to foster a culture of continuous improvement and sustainability. By incorporating these strategies into policy and operational practices, managers not only boost productivity but also meet stringent environmental regulations, thus achieving a competitive advantage for the organization by demonstrating its commitment and social responsibility.

1. Introduction

Contrarily to the previous century, when most businesses focused on mass production, today's increased product personalization and fast-changing product conditions have prompted businesses to adopt Lean Manufacturing (LM) (Mourtzis, 2020). The main idea of LM is to reduce costs by relating and excluding non-value-added activities (Leong *et al.*, 2019). LM focuses on seven types of waste associated with the manufacturing process: overproduction, waiting, transportation, defects, improper processing, inventory and unnecessary movement. In addition, the waste of labor capabilities is also considered.

In contrast, the SS methodology is a continuous improvement strategy that seeks to improve growth, capacity and customer satisfaction. It focuses on improving efficiency, reducing variability and eliminating the causes of errors, defects, or delays to reduce costs. While some companies compare these methodologies to determine which is superior, both seek to improve the business and its processes, which is necessary nowadays to solve organizational problems effectively. The key is using an integrated project management approach rather than separate systems. Lean Six Sigma (LSS) methodology is regarded as a mechanism for reducing process variation and eliminating waste, hence increasing productivity in various disciplines and service sectors. It intends to increase revenues by creating high-quality goods and minimizing non-value-added activities (Leong *et al.*, 2019).

The detrimental consequences of industrial operations on the environment point to the need for more sustainable development; in this regard, green manufacturing is a strategy that originated in the 1990s to address environmental problems caused by human activities. This strategy aims to minimize adverse environmental impacts and reduce production costs (Prakash *et al.*, 2022).

Sustainable manufacturing initiatives, which include social, economic and environmental considerations, have been included in industrial and governmental project decision-making. Sustainable manufacturing produces goods that are pollution-free, save energy, protect natural resources and are economically viable and safe for employees, society and customers (Egilmez *et al.*, 2013).

In this sense, organizations are facing pressure to achieve economic, environmental and social goals, which is driving the transition to cleaner production (Das, 2018). The combination of Lean and Green (LG) approaches focuses on minimizing waste, which can be a potential approach to improving organizations' environmental and social performance (Bhattacharya *et al.*, 2019), in addition to the economic aspect.

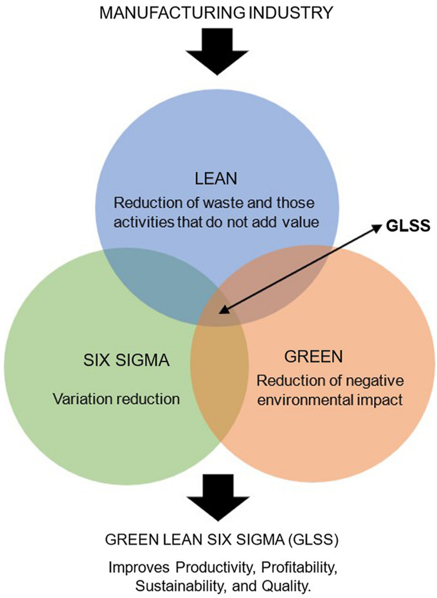
Although the relationship between Lean and environmental performance has recently started to be mentioned in the literature (Shokri and Li, 2020), particularly about the effect of Lean tools on the environmental aspect, research on the effects of these two practices on organizational performance is still in its early stages. Given the high costs of financing, raw materials, distribution and environmental and social challenges, the integration of lean and green can provide a competitive advantage to companies (Fercoq *et al.*, 2016).

Nevertheless, a single approach, whether Green, Lean or SS, can't inclusively address all aspects of sustainability. Therefore, an approach that reduces waste and variation and mitigates negative environmental impacts needs to be integrated (Figure 1); this is where GLSS, an inclusive technique used to reduce waste, optimize resource utilization and make problem-solving decisions in the manufacturing industry, comes into play (Kaswan and Rathi, 2020a, b).

The sequential and disciplined approaches defined by the define, measure, analyze, improve and control (DMAIC) procedure and similarly, the define, measure, analyze, design and verify (DMADV) procedure of SS and LSS are also integrated in GLSS but now, taking into account, not only the economic component but also the environmental and social elements in every step of these sequential approaches.

1.1 Research gap

Green, Lean and SS methods are combined in GLSS. These strategies drive increased profitability by reducing emissions, waste and reworks. Thus, GLSS allows the production of



Source(s): Authors' own elaboration

Figure 1. Integration of lean green six sima in the manufacturing industry

high-quality, low-cost and environmentally friendly products. Nevertheless, although strong theoretical foundations support the fusion of Green Lean and LSS, the literature still lacks sufficient empirical evidence regarding GLSS integration. Furthermore, according to Kaswan and Rathi (2020a, b), research around integrating these approaches is an area of exploration. Moreover, for Garza-Reyes (2015), the correlation between Lean and Green should be explicitly researched in sectors where it has yet to be adequately investigated. Likewise, for Cherrafi *et al.* (2019) there exists the need to create a model that combines Lean, SS and Green philosophies in organizations.

On the other hand, some key factors, known as enablers, determine the success of integrated management models (Kaswan and Rathi, 2020a, b). Therefore, it is crucial to identify the key facilitators in the implementation process initially (Swarnakar *et al.*, 2020). In this context, the challenge for companies is to understand and identify GLSS enablers and their relationships that can help adopt this integrated strategy successfully, thus getting a competitive advantage. Therefore, the main aim of our research is to bridge these gaps by investigating the enablers of GLSS integration and then proposing hypothetical causal relationships between these enablers that were empirically tested and statistically validated using information collected in the manufacturing context. Consequently, the following research questions framed our research:

RQ1. What are the most critical factors (enablers) when adopting GLSS in organizations?

RQ2. How can these enablers be measured during the adoption of GLSS in organizations?

RQ3. What are the causal relationships between these enablers during the adoption of GLSS in organizations?

The remainder of the article follows this structure: Section 2 comprises a literature review on GLSS enablers, the hypotheses to be tested and their theoretical foundation. Section 3 outlines the research methodology employed to validate the study's hypotheses. Section 4 details the results and significant findings, followed by a discussion in Section 5. Section 6 serves as the conclusion, addressing study limitations and proposing ideas for future research.

2. Literature review and hypotheses

The LG strategy focuses on the environmental, economic and social aspects of sustainability, according to Abualfaraa *et al.* (2020). This perspective arises from the Green-Lean fusion, supported by various studies demonstrating its ability to evaluate a project's benefits in multiple sustainability dimensions.

Despite the achievements obtained, some studies, such as those by Martínez-Jurado and Moyano-Fuentes (2014), point out the lack of metrics to quantify social sustainability as a deficiency. This highlights the need to develop projects that identify social indicators and provide a methodology to integrate the concepts of Lean, Green and Sustainability. Furthermore, Thanki *et al.* (2016) research highlights LG's benefits in reducing CO2 emissions and meeting delivery deadlines.

For manufacturing companies in this context, the challenge lies in understanding and identifying GLSS enablers that support successful adoption. It is essential to initially identify critical enablers in the implementation process, according to Swarnakar *et al.* (2020). This research used a comparative technique to evaluate the enablers of LM and SS, identifying specific enablers of the integrated LSS and Green Lean methodologies. Facilitators were defined as individuals with essential qualities to achieve organizational objectives.

After reviewing the literature, we identified the three most reported enablers as the most significant for implementing LG and LSS: LDR, organizational involvement (OI) and PM.

These enablers favor the economic, social and EB an organization can obtain by implementing projects under this integrated methodology. Conceptual definitions of these enablers were derived from the literature review and are presented in Table 1.

Also, it is essential to consider that every improvement project seeks to maximize the benefits for the organization, so according to the literature review, the concept of benefits was defined in the three pillars of sustainability. Table 2 shows the conceptual definition of these three pillars.

Leadership (LDR)	It is considered an essential factor in project implementation (Sharma *et al.*, 2021). Good leadership is crucial in selecting and supervising projects, creating a participatory environment and recognizing employee achievements. Leadership must involve all departments in the organization (Swarnakar *et al.*, 2020) and act as the driver of any improvement project
Organizational Involvement (OI)	It is considered a crucial component that influences achieving the results desired by the organization and the employees. It aims to understand and promote organizational and employee engagement, creating a work environment that promotes commitment, satisfaction and optimal performance (Cuya Araujo and Hiyane Casanova, 2019)
Performance Measurement (PM)	It refers to a system of procedures that makes it possible to evaluate the effectiveness and profitability of an investment. Its importance lies in providing relevant information for decision-making, diagnosing problems and measuring the impact in specific situations. In addition, it is an essential tool for collecting data and metrics, managing risks and opportunities, assessing productivity and financial impact and adapting to specific contexts to maximize organizational benefits (Sharma *et al.*, 2021)

Source(s): Authors' own elaboration

Table 1. Conceptual definitions of the enablers

Table 2.
Conceptual definitions of Benefits

Benefit Considered an advantage in favor of a person or a group of interested persons obtained by a change in the organization. Benefits should not only focus on economic aspects, but should also consider social and environmental aspects (Mohan *et al.*, 2022)	Economic benefit (EcB) It refers to the gains obtained during a process and is measured by reducing costs and waste and improving efficiency, quality and delivery times (Xu *et al.*, 2022) Environmental Benefit (EB) is understood as the mitigation of losses in the ecosystem, which can be measured by controlling the consumption of resources, restricting waste, reducing atmospheric emissions and protecting the environment (Whitehead and Rose, 2009). Social Benefit (SB) Is understood as the emotional relationship between employees, which can be measured through safety, health and work environment (Kusumawati *et al.*, 2021)

Source(s): Authors' own elaboration

Based on the above information, eight hypotheses were proposed for this research to determine the impact of the enablers on the EcB, EB and SB of implementing GLSS improvement projects in the Mexican Manufacturing Industry (MMI).

2.1 Development of hypotheses

For Swarnakar *et al.* (2020), LDR plays a crucial role in industries' success and is essential to organizational improvements. According to Srimathi and Narashiman (2021), LDR ensures success in implementing continuous improvement strategies as long as it has the organization's support and commitment. Loh *et al.* (2019) mention that LDR plays a fundamental role in the interaction between people, being necessary for solving problems and highlighting its importance at all levels of the organization and in the implementation to achieve project success. From this perspective, our first research hypothesis is as follows:

H1. LDR has a direct and positive effect on OI when implementing GLSS projects in the MMI.

López Bravo and Cassano (2019) highlight the importance of greater involvement by the organization to achieve project objectives. Similarly, De la Vega *et al.* (2023) state that involvement creates an environment of trust and encourages worker participation, which allows organizational goals to be achieved and is vital to success in implementing process improvement initiatives such as the integrated GLSS methodology. On the other hand, Flor Vallejo *et al.* (2020) suggest that implementing improvement strategies represents a significant challenge for organizations since it implies a change in mentality and culture that continually challenges the traditional way of working. From the above, it follows that the organization's involvement is critical in the success of improvement projects by providing the tools and resources necessary for their implementation. Following this discussion, we propose the second research hypothesis as follows:

H2. OI has a direct and positive effect on PM when implementing GLSS projects in the MMI.

Gastelum-Acosta *et al.* (2023) indicate that success in the execution of improvement projects is linked to various factors, called critical success factors (CSFs) or facilitators, among which the PM stands out as an opportunity to conclude a project, generating benefits such as cost reduction and waste, improvements in quality and an increase in employee motivation.

According to Ghadimi *et al.* (2020), by improving organizational performance, the costs associated with materials and energy in product manufacturing become more profitable and efficient from an environmental perspective. For their part, Swarnakar *et al.* (2020) argue that the level of OI is a crucial factor in improving performance, measured through employee performance, improved interdepartmental communication and process/production optimization, generating EcB without neglecting social and environmental aspects. Accordingly, we propose hypotheses three, four and five of our research:

H3. PM has a direct and positive effect on EcB when implementing GLSS projects in the MMI.

H4. PM has a direct and positive effect on SB when implementing GLSS projects in the MMI.

H5. PM has a direct and positive effect on EB when implementing GLSS projects in the MMI.

Gaikwad and Sunnapwar (2020) point out that the integration of methodologies brings benefits such as reduced waste and variations in processes, increased competitiveness, improved quality, energy savings and increased customer satisfaction. Therefore, the joint incorporation of Green, Lean and SS could benefit industries by improving their operational, social, environmental and economic performance. While Shokri and Li (2020) highlight the importance of adopting the integrated GLSS strategy due to the synergies they possess individually, underlining that their joint application has a crucial strategic value in manufacturing to improve profits, starting with the optimization of efficiency and sustainability of the organization, as well as quality improvement. In this sense, our sixth, seventh and eighth research hypotheses are stated as follows:

H6. In GLSS projects, SB has a direct and positive effect on EB.

H7. In GLSS projects, SB has a direct and positive effect on EcB.

H8. In GLSS projects, EB has a direct and positive effect on EcB.

3. Methodology

This section outlines the stages undertaken to reach the research objective. Figure 2 illustrates a flowchart encapsulating the procedural steps employed in this study, a methodology adapted from Hair *et al.* (2013).

A survey design was employed in this study to collect data on the usage of GLSS enablers in the implementation and development of improvement-oriented initiatives in Mexico's manufacturing industry. The methodology used for developing and validating the survey is frequently employed in the social sciences to measure variables using the psychometric method (Price, 2016). There were three stages to the survey design and validation procedure. The structural model was constructed and validated in stage 3. Each stage is described in detail below:

3.1 Survey development and sampling

The initial step in designing the instrument involved defining constructs and conducting a comprehensive literature review using databases like EBSCO Host, Elsevier, Emerald, IEEE, Springer and Google Scholar. The review covered ten years of articles on facilitators of improvement initiatives using LM and SS methodologies, with keywords including LM, Enablers, LSS, LG and GLSS. It should be noted that the enablers represent the latent factors

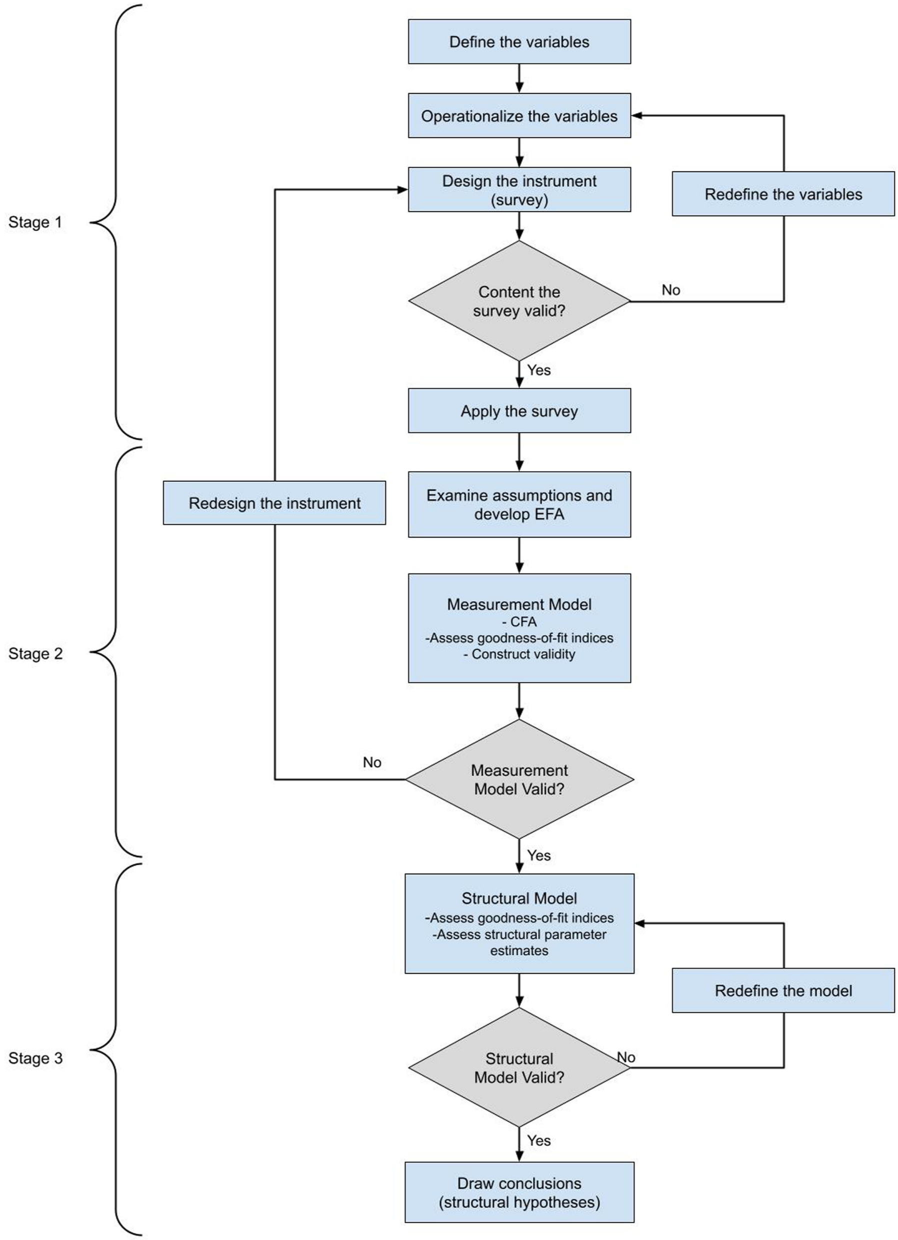


Figure 2.
Flowchart of the stages of the methodology

Source(s): Authors' own elaboration

identified by the survey. Because they could not be directly measured, they had to be operationalized (Padua, 2018); in other words, these subjective factors had to be transformed into directly observable variables. This operationalization required the conceptual definitions in Tables 1 and 2, resulting in the final survey.

This study used a five-point Likert scale, ranging from never (1) to always (5), to measure latent variables through related items (Carpita and Manisera, 2012). For content validity, LM and SS experts from academia and industry reviewed the survey, assessing question clarity, industry terminology and completion time. The survey was updated based on their feedback.

This study targeted employees in medium and upper management roles at Mexican manufacturing companies, specifically managers, production supervisors, project leaders and various engineers (process/production, continuous improvement, new products) with at least one year of experience in implementing GLSS.

3.2 Statistical analysis for the validation of the survey

A survey's validation entails two tests: reliability and validity. Authors Raykov and Marcoulides (2008) employed factor analysis to assess the reliability and validity of indirectly observable variables. Four critical components of survey validation were examined (Byrne, 2016): missing data, outliers, univariate and multivariate normality assumptions and multicollinearity. Statistical analyses were conducted using IBM SPSS® Statistics version 23 and complemented with Analysis of Moment Structures (AMOS).

To avoid missing data in the statistical analysis, only completely completed surveys were considered. The database was then evaluated for outliers using the Mahalanobis distance (Hair *et al.*, 2013). Next, the univariate normality of each of the variables in the instrument was measured based on skewness and kurtosis, as suggested by DeCarlo (1997). Mardia's test, which is based on the normalized value of multivariate kurtosis, was used to determine multivariate normality (Mardia, 1974). The approach involves comparing the Mardia coefficient for the study's data to a computed value derived from the formula $p(p+2)$, where p is the number of variables observed in the model (Raykov and Marcoulides, 2008). The proposed formula was used to generate the multivariate kurtosis value, which was compared to the value produced using the SPSS Amos software.

Finally, the data were checked for multicollinearity to eliminate the chance that two or more variables were significantly connected and measured the same concept. Variance inflation factors (VIF) are used to determine whether a variable is redundant if its values exceed 10 (Kline, 2016).

The correlation matrix was then subjected to an exploratory factor analysis (EFA) to establish the latent dimensions, and the results were utilized to determine the validity of each construct tested. So Brown (2015) defines instrumental validity as the degree to which an instrument measures whatever it claims to measure. Maximum likelihood estimation was employed in factor analysis to extract the component, which is vital and considered the most critical instrument in interpreting the EFA (Byrne, 2016). Varimax rotation was used in this investigation because it is less likely to produce inadequate solutions or uncorrelated components (Vandenbosch, 1996).

The Kaiser–Meyer–Olkin index (KMO), which measures whether partial correlations between variables are minor (Kaiser and Rice, 1974), was calculated as a first step in performing the EFA. In addition, the viability of the factor analysis was determined using Bartlett's test of sphericity. The EFA's next crucial step was eliminating unimportant factor loadings, referring to Hatcher and Stepanski (1994), who state that the loadings of each item should be at least 0.4 on its associated factor. After completing the EFA, a confirmatory factor analysis (CFA) was done using the SPSS Amos program. Univariate and multivariate normality, as well as outliers in the data and multicollinearity, were evaluated again.

Acceptable goodness-of-fit indices and specific tests for construct validity were used to determine the validity of a measurement model. According to Kline (2016), the minimum discrepancy coefficient/degrees of freedom (CMIN/DF) statistic, the root mean square error of approximation (RMSEA), the standardized root mean residual (SRMR), the Tucker–Lewis index (TLI) and the comparative fit index (CFI) should all be determined during the validation of a measurement model. It is also recommended to include the standard parsimony fit index (PNFI) when comparing models of varying complexity.

The Average Variance Extracted (AVE) index, which must exceed 0.5, was used to determine convergent validity, verifying that a set of items collectively represents a specific construct (Domínguez and Sanabria, 2019). Cronbach's Alpha and the Composite Reliability coefficient assessed internal consistency, the latter unaffected by the number of items (Vandenbosch, 1996). Nunnally (1978) suggests a minimum reliability of 0.7 for early research phases and 0.8 for basic research. Discriminant validity was checked by ensuring each construct's AVE exceeded the squared correlations between them, affirming construct independence.

3.3 Structural equation modeling (SEM)

After evaluating the measurement model, a structural model was created and validated to assess whether the enablers affect the benefits of improvement project implementation. SEM with the maximum likelihood estimation approach was employed, allowing for the simultaneous evaluation of each of the relationships rather than completing separate studies and thereby contrasting all of the hypotheses given in the research (Hair *et al.*, 2013). Finally, we assessed the statistical significance of the correlations and validated the provided hypotheses by examining the variables' direct, indirect and total effects.

4. Results

We conducted an exhaustive review of 50 academic articles to identify the most frequently mentioned facilitators in the literature. This review identified the three main enablers influencing GLSS projects' benefits: LDR, OI and PM (see Figure 3). These enablers were considered essential for the survey design (Table 1).

4.1 Development and application of the survey

The three enablers shown in Figure 3, defined in Table 1 and the benefits in Table 2 are the variables considered in the survey design. These variables are not directly measurable, so we had to operationalize them, transforming the subjective or latent variables into something we can measure directly. This process culminates in the final survey. To do so, based on the definitions in Tables 1 and 2, we identify indicators for each variable and formulate specific questions that allow these indicators to be measured.

The process of operationalizing a latent variable is illustrated below using the variable LDR. Four indicators were identified from the conceptual definition of the LDR variable: selection and prioritization project, motivation, participation environment and incentives. Each indicator is followed by the items used to measure it. Thus, the indicator "Selection and prioritization of projects" is measured using items LDR1 and LDR5, while the indicator "Motivation" is measured using items LDR2. LDR3 and LDR4 measure the "Participation environment" indicator, whereas LDR6 measures the "Incentives" indicator. The operationalization of the six full latent variables is shown in Table 3.

The instrument's final structure has five sections: The first offers an overview of the survey's goals; the second gathers demographic data on companies and respondents. The third evaluates the use of techniques in improvement projects and the fourth assesses

Authors	Leadership	Organizational Involvement	Performance Measurement
Macias-Aguayo *et al.* (2022)		✓	
Raval *et al.* (2018)	✓	✓	✓
Kaswan and Rathi (2019)		✓	✓
Farrukh *et al.* (2023)	✓	✓	
Rathi *et al.* (2022)		✓	✓
Mohan *et al.* (2022)		✓	✓
Das (2019)	✓	✓	✓
Kaswan and Rathi (2020)		✓	✓
Pranay and Tushat (2020)		✓	
Gastelum-Acosta *et al.* (2021)	✓	✓	✓
Kaswan *et al.* (2023)		✓	✓
De la Vega *et al.* (2023)	✓	✓	
Ahualfaraa *et al.* (2020)		✓	✓
Cherrafi *et al.* (2016)	✓	✓	✓
Bhattacharya *et al.* (2019)	✓	✓	✓
Cherrafi *et al.* (2019)	✓	✓	✓
Cuya and Hiyane (2019)		✓	
De la Vega *et al.* (2020)	✓	✓	
Fercoq *et al.* (2016)		✓	✓
Vallejo *et al.* (2020)	✓	✓	✓
Florida (1996)		✓	✓
Francescatto *et al.* (2023)	✓	✓	
Gaikwad and Sunnapwar (2020)		✓	✓
Garza-Reyes (2015)			✓
Garza-Reyes *et al.* (2017)		✓	✓
Gastelum-Acosta *et al.* (2023)		✓	✓
Ghadimi *et al.* (2020)	✓	✓	
Gholami *et al.* (2021)			✓
Shah and Ward (2003)			✓
Kaswan and Rathi (2020)		✓	✓
Letchumanan *et al.* (2022)		✓	✓
Singh *et al.* (2021)	✓	✓	✓
Shokri and Li (2020)	✓		✓
Srimathi and Narashiman (2021)	✓		
Limon-Romero *et al.* (2016)			✓
Alnadi and Mclaughlin (2021)	✓		
Laureani and Antony (2017)	✓		✓
Leong *et al.* (2019)	✓		✓
Loh *et al.* (2018)	✓		✓
Martinez-Jurado and Mayano-Fuentes (2014)	✓		✓
Sharma *et al.* (2021)	✓		✓
Mourtzis (2018)			✓
Swarnakar *et al.* (2020)	✓		✓
Tortorella *et al.* (2021)	✓		✓
Egilmez *et al.* (2013)			✓
Solaimani and Sedigi (2020)			✓
Teixeira *et al.* (2021)			✓
Thankki *et al.* (2016)			✓
Tortorella *et al.* (2017)			✓
Tlapa *et al.* (2016)			✓

Source(s): Authors' own elaboration

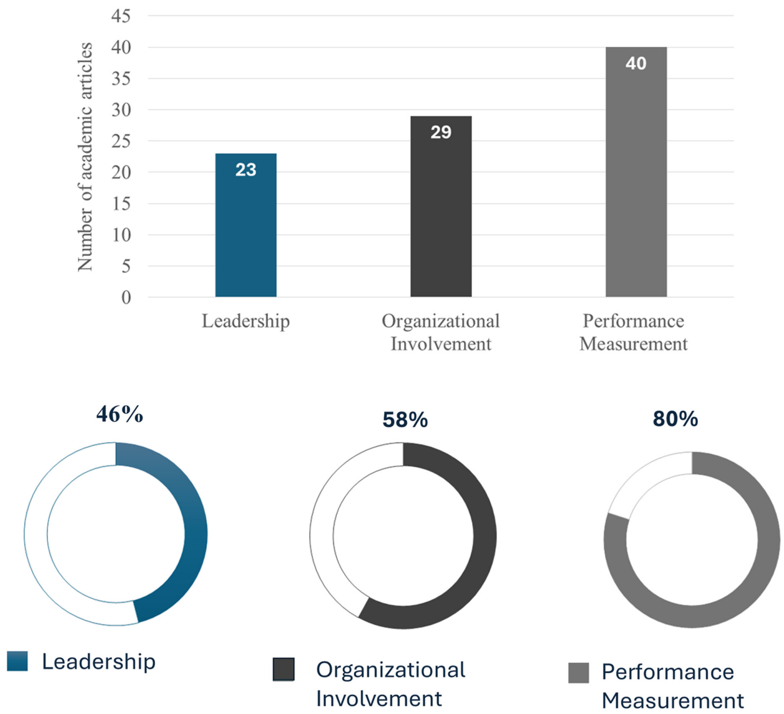


Figure 3. Main enablers influencing LGSS projects' benefits

Construct	Indicator	Item
LDR	Selection and prioritization Project	LDR1. In your company, the project leader or immediate boss assists in the selection and prioritization of projects
		LDR5. In your company, the project leader or immediate boss provides effective project leadership
	Motivation	LDR2. In your company, the project leader or immediate boss regularly motivates employees in their development
	Participation environment	LDR3. In your company, the project leader or immediate boss creates an environment of individual participation
		LDR4. In your company, the project leader or immediate boss increases staff participation and support
	Incentives	LDR6. In your company, the project leader or immediate boss assists in the selection and prioritization of projects
OI	Customer focus	OI2. In your company, performance benchmarking and continuous improvement are applied
		OI3. In your company, customer demand is understood
	Financing	OI6. In your company, senior management has sufficient funding and resources
	Performance	OI1. In your company, requirements are investigated for better results
		OI7. In your company, senior management conducts a periodic review of the performance of personnel
	Work environment	OI5. In your company, senior management encourages the development of a green environment and a safety system for employees
	Participation in projects	OI4. In your company, top management participates in the implementation of projects under improvement methodologies
PM	Development of procedures	PM2. In your company, you carry out structured improvement procedures
		PM3. In your company, they develop a clear roadmap to perform the implementation work
	Use of tools	PM1. In his company, the just-in-time tool is used
	Systems Development	PM4. In your company, create a performance measurement system
	Performance analysis	PM6. In their company, they analyze data and metrics
	Approach to solutions	PM5. In your company, experts provide the necessary help to solve doubts/problems
EcB	Costs	EcB1. Cost reduction
	Times	EcB2. Reduction of delivery times
	Quality	EcB3. ppm reduction
	Waste	EcB4. Waste reduction
	Efficiency	EcB5. Improvement in process efficiency
EB	Atmospheric emissions	EB1. Reduction of atmospheric emissions
	Resource consumption	EB2. Reduction in energy consumption
		EB3. Reduction in water consumption
	Solid waste	EB4. Solid waste reduction
SB	Security	SB1. Improved worker safety
		SB4. Reduction of risk areas
	Health	SB2. Improvement in workers' health
		SB3. Reduction of physical labor effort
	Work environment	SB5. Improved work environment and employee motivation

Source(s): Authors' own elaboration

Table 3.
Operationalization of variables

facilitators of project implementation. The last section explores the benefits businesses gain from using GLSS in improvement projects.

Approximately 500 surveys were distributed through email, social media and LinkedIn, yielding 146 completed questionnaires from 103 companies, a 29% response rate. Participants gave informed consent and the study adhered to the World Medical Association's (AMM) Helsinki Declaration (AMM, 2023).

The survey demographics showed that Production/Process Engineers were the most represented position, with more males participating. Most respondents had 2–5 years of experience and worked in large companies (over 250 employees). Baja California had the highest participation rate among Mexican states. Figure 4 displays the sample's characteristics.

4.2 Data validation

After filtering the data, four surveys identified as outliers were removed because they did not meet the level of statistical significance recommended by Kline (p < 0.001, 2016). Consequently, calculations were made to validate the survey with 142 responses. Improving the normality of the database was crucial, allowing the use of the maximum likelihood method for factor extraction (Schumacker and Lomax, 2016). Univariate normality was confirmed when skewness and kurtosis absolute values fell below 1.96 and 3, respectively, as shown in Table 4.

With 33 survey items, we checked for multivariate normality by computing Mardia's coefficient of kurtosis (Mardia, 1974) on SPSS Amos. This assumption was not violated since results revealed a multivariate kurtosis of 140.01, much lower than p (p+2) = 1,155 (Khine, 2013).

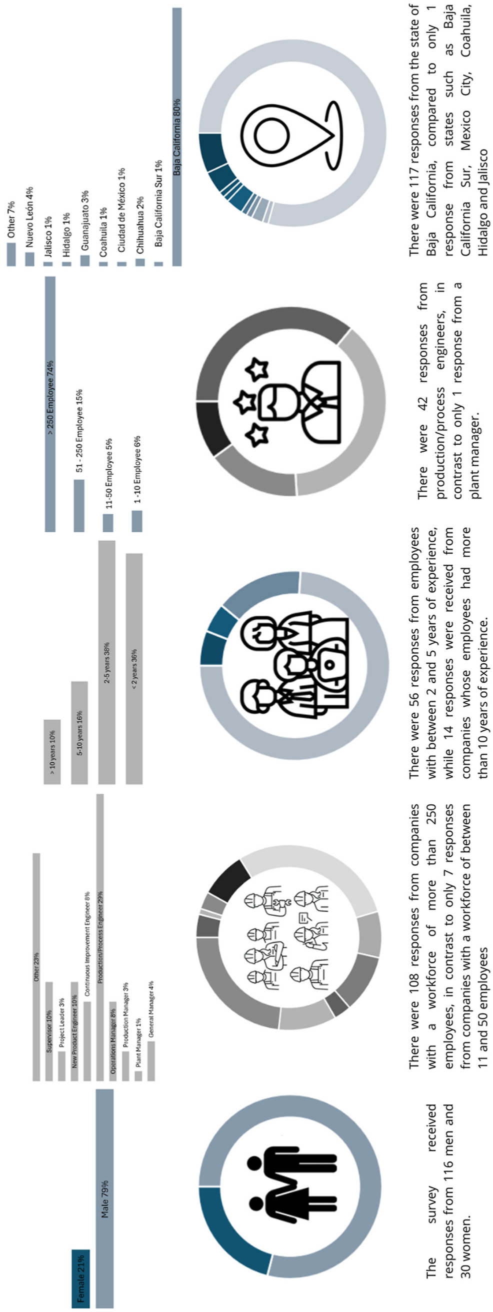
For testing multicollinearity, bivariate correlations and VIF values were calculated. The greatest bivariate correlation and VIF value were 0.89 and 8.935 respectively (Table 4). Therefore, it was possible to conclude that the data set does not exhibit multicollinearity issues (Kline, 2016).

In terms of sample adequacy, the KMO value = 0.912, which is more than 0.9, suggests that the current data are adequate for the analysis (Kaiser and Rice, 1974). The sphericity test by Bartlett was significant (p < 0.000), indicating sufficient correlation between the items and validating the appropriateness of the factor analysis. The factor loadings of the items were significant; therefore, they did not need to be eliminated.

4.2.1 Exploratory factor analysis (EFA). The EFA made it possible to identify six factors, constituted by a total of 33 variables with significant loadings and explaining 75.59% of the total variance of the data. According to Hair *et al.* (2013), a significant factor loading is a function of the sample size; as mentioned earlier, the study is based on 142 reliable surveys; therefore, factor loading values higher than 0.4 were considered significant for the analysis. It should also be noted that the eigenvalues of all factors were greater than 1 (Table 4).

4.2.2 Confirmatory factor analysis (CFA). Once the EFA was finished, the univariate and multivariate normality of the data, outliers and multicollinearity were rechecked. Any problems related to the two first normality assumptions were discarded, and the sample size was maintained for the subsequent tests.

The CFA results show that the measurement model fits perfectly, with a CMIN/DF of less than 3.0. Furthermore, the CFI and TLI values are greater than 0.9, the RMSEA is less than 0.08, and the SRMR is less than 0.08. These goodness-of-fit indices validate the measurement model. Finally, a PNFI value of 0.765 indicates that the amount of complexity is appropriate (Table 5). According to the findings, these six constructs can be utilized to assess the GLSS carrying out of improvement initiatives in Mexican business. The proposed measurement model depicts these constructs graphically (Figure 5).



Source(s): Authors' own elaboration

Figure 4.
Characterization of the sample

Construct/Variable	Skewness	Kurtosis	VIF	Factor loading	Eigenvalues
LDR					
LDR1	−0.579	−0.328	3.451	0.767	14.113
LDR2	−0.288	−0.717	4.392	0.876	
LDR3	−0.492	−0.150	3.411	0.808	
LDR4	−0.553	−0.196	5.365	0.905	
LDR5	−0.567	−0.18	4.992	0.858	
LDR6	−0.238	−0.849	4.000	0.828	
PM					
PM1	−0.344	−0.817	2.593	0.696	1.485
PM2	−0.864	0.342	5.431	0.913	
PM3	−0.791	0.123	2.986	0.801	
PM4	−1.24	1.367	4.216	0.812	
PM5	−0.708	0.047	3.429	0.762	
PM6	−1.166	0.866	4.422	0.752	
OI					
OI1	−1.107	1.050	3.550	0.785	1.858
OI2	−0.552	−0.495	3.142	0.711	
OI3	−1.28	1.368	3.049	0.762	
OI4	−0.667	−0.217	4.622	0.866	
OI5	−0.757	−0.079	3.786	0.808	
OI6	−0.912	0.287	3.773	0.815	
OI7	−0.851	0.440	3.786	0.806	
EcB					
EcB1	−0.796	0.794	3.260	0.734	1.314
EcB2	−0.304	−0.860	2.646	0.635	
EcB3	−0.706	0.041	2.515	0.752	
EcB4	−0.658	0.577	3.322	0.84	
EcB5	−0.802	0.632	3.164	0.795	
SB					
SB1	−0.783	0.199	7.319	0.849	1.01
SB2	−0.748	0.068	7.510	0.871	
SB3	−0.506	−0.487	5.161	0.911	
SB4	−0.633	−0.228	5.239	0.893	
SB5	−0.525	−0.155	3.244	0.733	
EB					
EB1	−0.011	−0.927	7.527	0.914	5.164
EB2	−0.107	−0.985	8.935	0.947	
EB3	−0.113	−0.993	8.050	0.926	
EB4	−0.165	−0.809	6.094	0.889	

Source(s): Authors' own elaboration

Table 4. Factorial structure and analysis of normality of the data

4.2.3 Construct validity. Table 6 displays the AVE values of the constructs or latent variables in this research along the main diagonal, demonstrating adequate convergent validity in all latent variables thanks to Cronbach's alpha values above 0.9 for the instrument developed. Table 6 shows that the constructs have a greater significant AVE value for discriminant validity than the square of all their correlations, suggesting that each construct of the instrument is distinct and may be used to explore a subset of the phenomenon. Finally, the nomological validity of the positive and significant correlations between constructs inside a measurement theory was determined.

4.3 Assessing the structural model

For the SEM, the study hypotheses describing the connections between latent variables or constructs were put to the test (Byrne, 2016) as can be seen in Figure 6.

Table 7 depicts the results including the standardized regression coefficients (SRW), critical ratio (CR) and probability value (P), help to confirm whether the model fits the data effectively. According to our findings, seven of the eight hypotheses have statistically significant connections. Environmental benefit-PM indicated a non-significant connection.

Figure 7 depicts the final model after the non-significant hypotheses were eliminated. Table 5 shows the fit indices of the final model (SEM), which suggest a good fit with a CMIN/DF less than 3.0. The CFI and TLI values are greater than 0.9, the RMSEA and the SRMR are less than 0.08. Finally, a PNFI rating of 0.755 indicates that the amount of complexity is appropriate.

Table 8 displays the direct and indirect effects of the significant variables. LDR had an indirect effect on PM, EcB, SB and EB; on the other hand, OI had an indirect effect on EcB, SB and EB; and the PM variable had an indirect effect on EB. Finally, the variable SB had an indirect effect on EcB.

The findings show that improvement initiatives are being conducted in the MMI utilizing the integrated GLSS approach. However, enterprises have yet to formalize their adoption inside the GLSS integration framework. Furthermore, these findings indicate that businesses are already analyzing the benefits of development initiatives not only in terms of economic value but also of environmental and social effects.

5. Discussion

This study evaluated the relationships among LDR, OI and PM to model their impact on EcB, SB and EB when implementing GLSS projects (Figure 7).

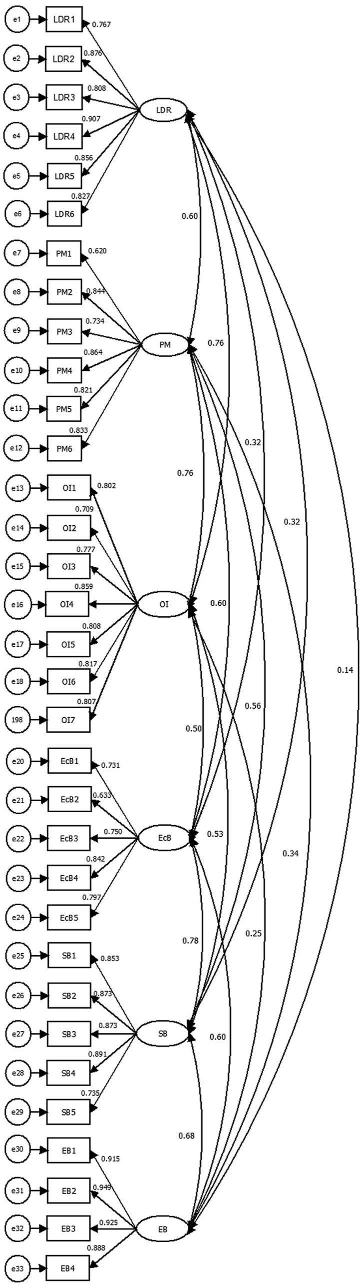
Our findings show that LDR has a positive effect on OI, which in turn positively affects PM. We also found that the PM affects EcB and SB. However, our results show no direct relationship between the PM and the expected EB. Instead, this is an indirect relationship through the EcB and SB.

Our results confirm that GLSS interventions depend primarily on LDR in the early stages of the implementation, thus being in line with previous studies (Flor Vallejo *et al.*, 2020; Gastelum-Acosta *et al.*, 2022). LDR is essential to ensure the successful adoption of new continuous improvement techniques, to promote problem-solving and the achievement of objectives and to maintain a clear vision with the support and commitment of top management (Alnadi and McLaughlin, 2021; Laureani and Antony, 2019). The actions of different leaders support decision-making at all levels through the use of facts and data

Table 5. Goodness-of-fit indices of the measurement model and the final structural model (SEM)

Goodness of fit indices	Recommended value	References	Measurement model	Final structural Model (SEM)
CMIN/DF	<3	Bollen (1989)	1.585	1.595
TLI	>0.9	Hair *et al.* (2013)	0.925	0.924
CFI	>0.9	Hair *et al.* (2013)	0.932	0.932
RMSEA	<0.08	Hair *et al.* (2013)	0.064	0.065
SRMR	<0.08	Dominguez and Sanabria (2019)	0.063	0.056
PNFI	Of 0.5 to 1	Mulaik *et al.* (1989)	0.765	0.755

Source(s): Authors' own elaboration



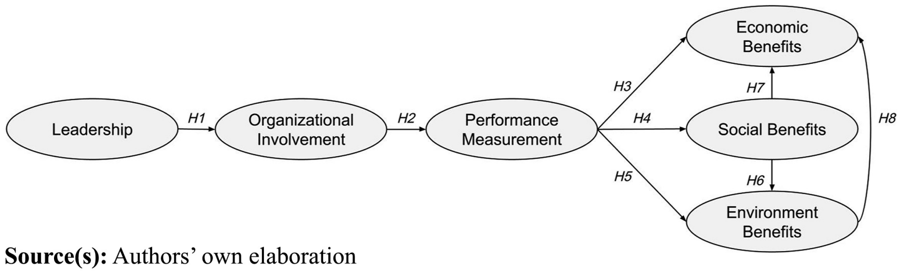
Source(s): Authors' own elaboration

Figure 5.
Proposed
measurement model

	EcB	EB	SB	LDR	PM	OI	Cronbach's alpha	Composite reliability
EcB	*0.5683*	0.3672	0.6084	0.1030	0.3612	0.2470	0.868	0.867
EB	0.6060	*0.8450*	0.4597	0.0164	0.1122	0.0600	0.956	0.956
SB	0.7800	0.6780	*0.7303*	0.1024	0.3181	0.2820	0.932	0.931
LDR	0.3210	0.1280	0.3200	*0.6370*	0.3648	0.1024	0.932	0.935
PM	0.6010	0.3350	0.5640	0.6040	*0.7080*	0.5791	0.907	0.908
OI	0.4970	0.2450	0.5310	0.3200	0.7610	*0.6250*	0.922	0.924

Note(s): The correlation between constructs is represented by values below the main diagonal, with a significance level of 0.01. The values on the main diagonal correspond to the constructs' AVE. The squared correlations are shown by the values above the main diagonal
Source(s): Authors' own elaboration

Table 6.
Discriminant and convergent validity of constructs



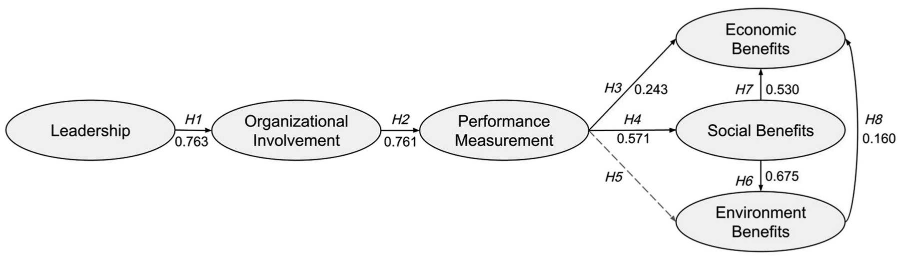
Source(s): Authors' own elaboration

Figure 6.
Proposal theoretical structural model of GLSS adoption

Hypothesis				S.R.W	S.E.	C.R.	P	Results
H1	LDR	→	OI	0.879	0.12	7.321	***	Supported
H2	IO	→	PM	0.632	0.088	7.148	***	Supported
H3	PM	→	EcB	0.211	0.073	2.877	***	Supported
H4	PM	→	SB	0.745	0.120	6.227	***	Supported
H5	PM	→	EB	−0.106	0.152	−0.694	0.487	Not supported
H6	SB	→	EB	0.959	0.131	7.332	***	Supported
H7	SB	→	EcB	0.359	0.078	4.587	***	Supported
H8	EB	→	EcB	0.080	0.045	1.787	*	Supported

Source(s): Authors' own elaboration

Table 7.
Hypothesis testing



Source(s): Authors' own elaboration

Figure 7.
Final structural model of GLSS adoption

	OI		PM		EcB		SB		EB	
	Unstd	Std	Unstd	Std	Unstd	Std	Unstd	Std	Unstd	Std
Leadership										
Direct effects	0.879	0.763	–	–	–	–	–	–	–	–
Indirect effects	–	–	0.554	0.581	0.295	0.353	0.410	0.332	0.373	0.224
Total effects	0.879	0.763	0.554	0.581	0.295	0.353	0.410	0.332	0.373	0.224
Organizational involvement										
Direct effects	–	–	0.630	0.761	–	–	–	–	–	–
Indirect effects	–	–	–	–	0.336	0.463	0.467	0.435	0.424	0.294
Total effects	–	–	0.630	0.761	0.336	0.463	0.467	0.435	0.424	0.294
Performance measurement										
Direct effects	–	–	–	–	0.214	0.243	0.741	0.571	–	–
Indirect effects	–	–	–	–	0.319	0.365	–	–	0.673	0.386
Total effects	–	–	–	–	0.533	0.608	0.741	0.571	0.673	0.386
Social benefits										
Direct effects	–	–	–	–	0.358	0.530	–	–	0.909	0.675
Indirect effects	–	–	–	–	0.073	0.109	–	–	–	–
Total effects	–	–	–	–	0.431	0.639	–	–	0.909	0.675
Environmental benefits										
Direct effects	–	–	–	–	0.080	0.160	–	–	–	–
Indirect effects	–	–	–	–	–	–	–	–	–	–
Total effects	–	–	–	–	0.080	0.160	–	–	–	–

Note(s): Unstd. Unstandardized; Std. Standardized
Source(s): Authors' own elaboration

Table 8. Effects for the proposed final structural model

(Gastelum-Acosta *et al.*, 2022) and promote commitment with other stakeholders, such as suppliers, playing a key role in guaranteeing the suppliers' participation in lean improvement project (De la Vega *et al.*, 2020). LDR supports organizational commitment and involvement in the pursuit of continuous improvement and success in project implementation (Francescatto *et al.*, 2023) by providing guidelines and resources and fostering OI in GLSS implementation.

OI was confirmed as an enabler of GLSS, in line with previous studies (Kaswan and Rathi, 2020b; Letchumanan *et al.*, 2022). OI positively affects PM. In this regard, Cuya Araujo and Hiyane Casanova (2019) found that involvement builds trust, leading to a stable and productive work environment, while Singh *et al.* (2021) emphasized that OI guarantees the availability of human, technical and economic resources to develop improvement projects. Similarly, Swarnakar *et al.* (2020) highlighted that involvement helps increase staff participation and promote interdepartmental collaboration, while Kaswan and Rathi (2020b) identified the organizational readiness for GLSS as the top enabler.

Therefore, for implementing such a recent strategy as GLSS, management involvement plays a significant role in the organization's allocation of adequate human, technical and economic resources (Singh *et al.*, 2021).

In terms of PM, our study confirmed its direct positive effect on EcB and SB and its indirect effect on EB. Thus, our study agrees with previous studies that identified the positive effects of LSS and a sustainable approach on EcB (Cherrafi *et al.*, 2016; Tlapa *et al.*, 2016). In this regard, there is an agreement that LSS is positively associated with operational performance, particularly economic performance (Tortorella *et al.*, 2020), such as reducing inventory (Shah and Ward, 2003), variation (Limon-Romero *et al.*, 2016), waiting time (Tlapa *et al.*, 2022) among others. Additionally, our findings confirmed that SB directly impact economic and EB. In this regard, Solaimani and Sedighi (2020) stated that some GLSS techniques can have a positive impact on the pillars of sustainability, such as better worker safety (social benefit) and work standardization, which implies a reduction in variability, resulting in lower production costs (economic benefit). Thus, in addition to fulfilling economic objectives, organizations must also meet customer goals (Garza-Reyes *et al.*, 2017), social goals and environmental goals Teixeira *et al.* (2021). These advancements may result in less reprocessing (economic benefit), less resource waste (environmental benefit) and fewer hazardous operations (social benefit). Despite the inherent relationship between GLSS and EB (Gholami *et al.*, 2021), our results show no direct positive effect but indirectly through the EcB. In this sense, a common barrier to better performance in the social and environmental pillars on organizations comes from the idea that these improvements could affect economic performance (Florida, 1996). In this regard, some recommendations include understanding the relationship between the level of adoption and the contextual variables to anticipate occasional difficulties and set the proper expectations along the implementation (Tortorella *et al.*, 2017); transforming traditional LSS projects into green projects by leveraging volume of products and consumer price (Shokri and Li, 2020); integrating LSS projects with the International Organization for Standardization (ISO) 50001 energy management system standard (Trubetskaya *et al.*, 2023); or supporting green approach of LSS with technologies related to industry 4.0 to have an important role in EB (Tortorella *et al.*, 2021).

Our results are partially consistent with previous studies conducted in India; Singh *et al.* (2021) found that in addition to LDR and management involvement and commitment, a general environmental awareness program, carbon reduction initiatives and employee training and incentives enable effective implementation in micro and small companies. Gaikwad and Sunnapwar (2020) reported results similar to ours; however, their study found a direct effect of operational performance on EB. In this sense, GLSS projects are not free of conflicts among the expected benefits, e.g. economic-oriented results such as quality improvement or process optimization might have some level of exclusion with environmental results such as reducing energy consumption. In their study, Khawar *et al.* (2016) recommended a higher level of temperature to reduce the rejection and scrap rate for steel manufacturing; however, there is a conflict between less energy use and CO2 emissions by applying a higher temperature in principle (Shokri and Li, 2020).

Despite confirming the economic benefit of GLSS, more is required to achieve merely economic gains Teixeira *et al.* (2021). Moreover, despite the broadly acknowledged capabilities of GLSS in the manufacturing industry, practitioners continue to be cautious about its implementation owing to insufficient knowledge and culture (Letchumanan *et al.*, 2022). Integrating the environmental component might yield business benefits such as developing environmentally friendly procedures and lowering the negative impact of manufacturing on the environment, resulting in cleaner production (Singh *et al.*, 2021). Derived from our findings, we highlight the importance of studying the facilitators and barriers of GLSS, promoting proper education and training related to the EB and incorporating an environmental and social agenda in GLSS implementations. In this sense, education in GLSS topics prepares not only for organizational demands but also for more prepared employees (Tortorella *et al.*, 2020). In summary, adopting the GLSS methodology as an integrated approach offers promising results in improving companies' performance by providing insights into economic, social and environmental aspects.

5.1 Managerial and practical implications

A practical implication of this paper is that it provides the main enablers of GLSS focused on manufacturing companies. Whether a continuous improvement strategy succeeds or fails is ultimately the responsibility of the organization's top management. If enablers are clearly identified, GLSS implementation may become more organized and successful due to this knowledge and comprehension. Thus, the model validation complements valuable insights and fresh perspectives for managers, practitioners and organizations pursuing the implementation of GLSS in developing countries instead of emulating the actions reported by companies located in developed countries, which will not necessarily produce similar outcomes. Moreover, a managerial implication of the model is a complete sequence of causal relationships among GLSS enablers in order to establish internal policies until the benefits associated with a successful deployment of the GLSS strategy are reached, thus gaining a competitive advantage for organizations. In addition, the developed structural model aims to foster new studies in the progress of an effective GLSS implementation.

5.2 Limitations

The study presents some limitations. First, the results were validated in the manufacturing sector of a developing country. Thus, more implementations and research in other countries are recommended to obtain a broader and comparative view. Second, the data collection included only complete surveys from those who agreed to participate thus a response bias could have been introduced. An alternative would be to use additional methods that minimize this potential bias. Third, the literature review was conducted in six databases; despite covering most of the studies, there are chances of exclusion of relevant publications in databases not considered.

6. Conclusions and future work

This study provided a solid empirical base to understand the adoption of the GLSS methodology, highlighting the three crucial enablers for implementing GLSS. Based on our results, LDR, OI and PM play a significant role in obtaining EcB, EB and SB in improvement projects. Our findings support the importance of having committed and trained leaders who drive implementing the GLSS projects in organizations and consider sustainability aspects to achieve significant benefits. The OI, supported by the top management LDR, plays a significant role for the PM, which in turns affects positively the social and EcB. Outstandingly, our results did not support the hypothesis that PM have a direct effect on EB, but indirect. Therefore, incorporating environmental concerns as well as social concerns into the organization’s priorities and agenda, might promote a sustainable performance.

In future research, other factors and variables relevant to successfully adopting the GLSS methodology, such as organizational culture, employee training and change management, could be examined. Furthermore, it would be beneficial to explore the impact of the GLSS methodology in different industry sectors and assess its applicability in companies of different sizes.

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