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Digital Cartography, Visual Analytics, and Collaborative Interfaces: Geospatial Data and Operational Risk

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KEYWORDS

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Smart logistics

ABSTRACT

Introduction: *Logistics management requires the integration of geospatial information, indicators, and risk signals to support decision-making.* ***Objectives:*** *To design and preliminarily evaluate a collaborative visual architecture for managing routes and operational risk in Santa Elena, Ecuador.* ***Methodology:*** *A sequential multi-method design was applied, integrating a review (2020–2025), a survey of 50 participants, prototyping, an assessment by 10 specialists, and an illustrative comparative scenario.* ***Results:*** *83.7% perceived congestion levels as medium, high, or very high; 80% valued monitoring, and 90% valued risk prevention. In the comparative scenario, travel times were 95 and 72 minutes, fuel consumption was 18 and 13 liters, and estimated CO_2 emissions were 48.24 and 34.84 kg.* ***Discussion****: The findings support the conceptual relevance of integrating mapping, indicators, and alerts, although the operational effectiveness of the interface was not demonstrated.* ***Conclusions:*** *The architecture represents a preliminary proposal that requires further usability evaluation and testing in additional scenarios.*

1. Introduction

The digitalization of logistics has turned freight transport into a process accompanied by continuous flows of data from sensors and other digital technologies (Rejeb et al., 2022). Variables such as vehicle position, congestion, fuel consumption, incidents, restrictions, and emissions can be updated from diverse sources (Winkelhaus & Grosse, 2020). The challenge no longer lies solely in having information available, but in organizing it visually in order to recognize priorities, compare alternatives, and maintain geographic context during decision-making (Nadj et al., 2020). In this framework, the interface mediates between data and their operational interpretation, and may influence risk perception and cognitive load (Cheong et al., 2020; C.-F. Wu et al., 2022; R. Wu et al., 2023).

Logistics 4.0 is characterized by interconnected networks supported by the Internet of Things, digital platforms, analytics, and artificial intelligence (Ben-Daya et al., 2019; Lagorio et al., 2022). Although these technologies expand the capacity to calculate routes and coordinate operations, they also increase the information density of interfaces (Abideen et al., 2023; Tsolaki et al., 2023). Visual design must therefore prioritize information and represent spatial relationships, uncertainty, and risk in a comprehensible manner (Eberhard, 2023; Kinkeldey et al., 2017; Padilla et al., 2018).

An effective representation must relate data type, task, and visual channel (Ware, 2021) . Position, color, size, shape, and icons make it possible to communicate spatial relationships, intensity, magnitude, and types of events (Roth et al., 2023). However, maps and dashboards are not neutral: they select which information is made visible and what is prioritized (Juergens, 2020; Kühne & Edler, 2025; Milutinović et al., 2021). From the standpoint of visual culture, these interfaces can be understood as artifacts that mediate between technical systems, organizational practices, and human decisions (Herrmann & Pfeiffer, 2023; Manovich, 2020; Söderlund & Hansson, 2021).

In logistics management, routing algorithms make it possible to compare distances, times, capacities, and operational constraints (Liu et al., 2023); however, a mathematically efficient solution must be translated into information that is comprehensible and actionable for decision-makers (Coussement & Benoit, 2021; Simkute et al., 2021). In addition, these models may contain operational constraints that are implicit or not explicitly represented, and identifying them is relevant for properly interpreting the proposed solutions (Konovalenko et al., 2025). Visual analytics can integrate calculations, geography, and graphic cues to contextualize recommendations (Bill et al., 2022; Maack et al., 2023). In Santa Elena, Ecuador, this need involves jointly representing mobility, safety, geospatial information, and dynamic transport conditions (Molina-Campoverde et al., 2024; Sohrabi et al., 2022). For this reason, the central aim of the study is not to demonstrate the superiority of an algorithm, but to design a collaborative visual architecture that makes recommendations, indicators, and risk legible.

Although progress has been made in route optimization, intelligent transport, visual analytics, dashboards, and the cartographic representation of risk, these areas tend to be studied in a fragmented way (Kleinová & Straka, 2024). The integration of operational indicators and risk signals within a common geospatial architecture that facilitates interpretation, coordination, and decision-making remains insufficient (Coussement & Benoit, 2021; Yuan et al., 2021). This study addresses that gap through the design and preliminary assessment of a collaborative visual architecture that brings together cartography, indicators, and risk encoding.

The main research question was: How can a collaborative cartographic interface represent geospatial data, operational indicators, and risk signals in such a way that different actors construct a shared operational picture? Three sub-questions were derived from it: a) What visual problems and needs are perceived by participants involved in transport, distribution, and logistics operations? b) What information architecture and what graphic codes are suitable for prioritizing routes, indicators, and alerts? c) What level of relevance and acceptance does the proposal show, and what operational changes are observed in an illustrative comparative scenario?

The general objective was to design a collaborative visual architecture that integrates cartographic representation, visual analytics, and risk information to support logistics management. The specific

objectives were: i) to characterize the scientific context and user needs; ii) to define the information hierarchy, the risk encoding, and the interface components; iii) to analyze the expert assessment of relevance and acceptance; and iv) to compare indicators for the reference scenario and the proposed alternative. The contribution lies in a visual translation model that connects geospatial data and operational decisions without equating conceptual acceptance with usability.

2. Theoretical framework

2.1. The logistics interface as a visual artifact

A monitoring interface selects, organizes, and prioritizes data in order to facilitate the interpretation of complex situations, especially when decisions are time-dependent (Franconeri et al., 2021; Patel et al., 2024). Its effectiveness depends on the correspondence between information and visual encoding: spatial alignment facilitates comparisons, while color and shape make it possible to distinguish categories, although their effectiveness decreases in the face of excessive complexity (Giovannangeli et al., 2022; Matlen et al., 2020). The design must therefore respond to specific tasks, such as comparing routes, identifying deviations, and prioritizing risks.

In logistics, visual analytics integrates data from diverse sources to support decisions and can influence the user's performance and situational awareness (Khakpour et al., 2021; Nadj et al., 2020). In this study, the shared operational picture is defined as the common representation of routes, statuses, and risks used to support coordination among the actors involved in the operation.

2.2. Geospatial cartographic representation

Geospatial visualization integrates geographic information, attributes, time, and uncertainty, and must therefore balance information density and legibility (Schöttler et al., 2021). In transport, cartographic design and dynamic information can affect search efficiency and cognitive load (C.-F. Wu et al., 2022). For this reason, the proposal uses filters, zoom levels, and progressive disclosure, and represents risk through a redundant encoding of color, icon, text, and position, avoiding exclusive reliance on color and differentiating between the calculated, recommended, and confirmed route (Franconeri et al., 2021; Giovannangeli et al., 2022).

2.3. Visual analytics, dashboards, and situational awareness

Visual analytics combines computational processing, visualization, and interaction, and its usefulness depends on the task and the level of interaction allowed (Perkhofer et al., 2020; Yuan et al., 2021). In operational dashboards, excessive automation can reduce situational awareness (Nadj et al., 2020). The prototype therefore prioritizes an overview with a map, indicators, and alerts. The study does not claim a proven reduction in cognitive load, since this variable was not measured.

2.4. Human-centered design and evaluation

Human-centered design requires consideration of users, tasks, and context of use, as well as the iterative evaluation of solutions (International Organization for Standardization, 2019). Usability comprises effectiveness, efficiency, and satisfaction, and should not be confused with acceptance or perceived usefulness (Bevan et al., 2016; Perkhofer et al., 2020). In this study, the specialists' assessment examined only conceptual relevance and acceptance. A usability evaluation will require a functional prototype, observable tasks, and metrics of effectiveness, time, errors, and satisfaction.

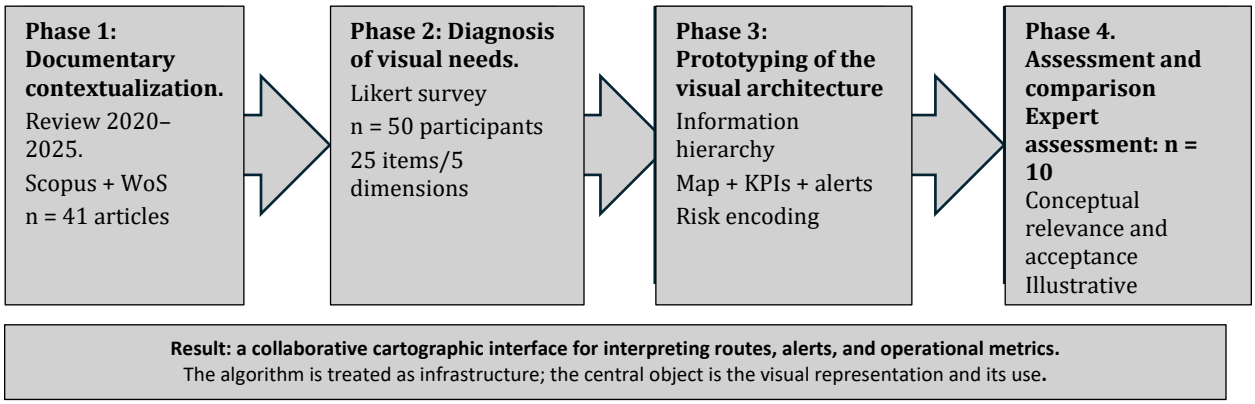
3. Materials and methods

3.1. Research design

An applied, sequential, multi-method design was developed, aimed at the formulation and preliminary assessment of a visual interface architecture (Kajamaa et al., 2020). The methodological sequence

integrated a documentary contextualization, a descriptive quantitative diagnosis by means of a survey, the prototyping of the visual architecture, an expert assessment of conceptual relevance and acceptance, and an illustrative comparative scenario (Van der Merwe et al., 2020). Each procedure generated a different type of evidence, which was integrated sequentially and in a complementary manner to guide the design and assessment of the proposal, without establishing causal relationships or equating descriptive, expert, and comparative evidence (Guetterman et al., 2020; Skamagki et al., 2024). The study was structured in four phases.

Figure 1. Applied sequential multi-method design oriented toward the visual architecture of the interface.



Source: Authors' own elaboration.

The four phases generated complementary evidence: documentary contextualization (Donthu et al., 2021), needs diagnosis (Taherdoost, 2022), prototyping of the architecture (Van der Merwe et al., 2020), expert assessment of conceptual relevance and acceptance, and an illustrative comparative scenario (Maldonado-Suárez & Santoyo-Telles, 2024). The evidence was interpreted sequentially and descriptively, without establishing causality or equating conceptual assessment with operational effectiveness (Guetterman et al., 2020).

3.2. Phase 1: Documentary contextualization 2020–2025

The documentary contextualization was carried out in Scopus and the Web of Science Core Collection (WoS) to identify literature on route optimization, intelligent transport, operational safety, risk prevention, and digital or collaborative platforms. The search was conducted on June 7, 2026, following the logic of PRISMA 2020 (Page et al., 2021), and the records were processed in RStudio using Bibliometrix/Biblioshiny (Aria & Cuccurullo, 2017). This phase had a contextual purpose and was not intended as a meta-analysis.

In the Web of Science Core Collection, the search was carried out using the Smart Search function, with the following natural-language query (entered in Spanish): *"Diseño de plataforma colaborativa para la optimización de rutas logísticas que integra la seguridad operativa y la prevención de riesgos en el transporte"*. The search history recorded 62 results for this query. The platform processed the query semantically through the Topic (TS) field, generating the following combination of concepts: TS=("collaborative platform") AND TS=("optimizing logistics routes") AND TS=("operational safety") AND TS=("risk prevention") AND TS=("transportation"). Since this was a Smart Search query, exact reproduction depends on the semantic processing performed by the platform; the natural-language query and the recorded TS combination are therefore retained as elements of traceability, and this condition is acknowledged as a limitation on reproducibility.

In Scopus, retrieval was carried out in the title, abstract, and keyword fields. The traceability of the session made it possible to recover the terms used during the search: *route optimization*, *logistics route*, *operational safety*, *risk prevention*, *transport safety*, *collaborative platform*, *digital platform*, and *intelligent transportation systems*. The original export used in the study consisted of 45 bibliographic records. To ensure the reproducibility of the strategy, the recovered terms were subsequently organized into the

following equivalent Boolean formulation: TITLE-ABS-KEY (("route optimization" OR "logistics route") AND ("operational safety" OR "risk prevention" OR "transport safety") AND ("collaborative platform" OR "digital platform" OR "intelligent transportation systems")).

The Scopus search string was reconstructed from the available traceability and the exported set, since the complete original query was not stored; it is therefore not presented as a literal transcription.

The records from both databases were imported into RStudio 4.6.0 using convert2df() and merged with Bibliometrix's mergeDbSources(). Four duplicates were identified and removed before document screening.

Articles published between 2020 and 2025 that were relevant to logistics, transport, route optimization, safety, or operational risk, with sufficient bibliographic information and identified by a DOI, were included. Duplicates, documents without a DOI, document types other than articles, publications outside the thematic scope, editorials, notes, residual records, and documents outside the time window were excluded. The use of the DOI as an operational criterion favored traceability, although it may have excluded relevant literature and is acknowledged as a limitation of the documentary contextualization.

A total of 107 records were retrieved: 45 from Scopus and 62 from WoS. After the removal of 4 duplicates, 20 documents without a DOI, 6 records that were not articles, 30 documents that were thematically irrelevant or residual, and 6 publications from 2026, the final sample consisted of 41 articles published between 2020 and 2025.

3.3. Phase 2: Needs diagnosis

The diagnosis was carried out by means of a structured survey of 50 participants involved in transport, distribution, and logistics operations, selected through non-probabilistic convenience sampling (Andrade, 2021). People connected with these activities who agreed to participate voluntarily were included. Owing to the exploratory and local nature of the sample, the results were interpreted descriptively and not as representative estimates of a larger population.

The instrument included 25 items distributed across five dimensions: logistics efficiency, operational safety, monitoring and technology, risk prevention, and intelligent collaborative platform. The items were derived from the study variables and the documentary contextualization. A five-level Likert scale was used: 1 = very low, 2 = low, 3 = medium, 4 = high, and 5 = very high (Cooksey, 2020; Jebb et al., 2021). The 25 items are presented in Appendix A.

The form also collected contextual information on workplace and type of operation, but did not include standardized variables on professional category or years of experience. The responses were analyzed using frequencies and percentages; missing data were handled on a valid-case basis, without imputation, and no population inferences were made.

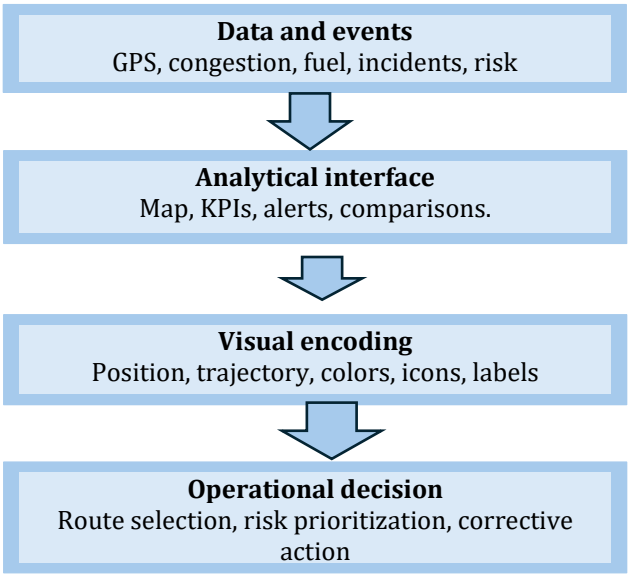
No documentary evidence is available of formal content validation, prior psychometric validation, or internal consistency calculated during administration. Undocumented coefficients were therefore not added retrospectively, and the results are interpreted exclusively for descriptive and exploratory purposes.

3.4. Phase 3: Prototyping of the visual architecture

The prototype was developed as a conceptual representation and not as evidence of a deployed system (vom Brocke et al., 2020). The architecture integrates three layers: i) a cartographic layer, with the map, routes, origin, destination, risk zones, and events (Schöttler et al., 2021); ii) an analytical layer, with indicators of time, fuel, emissions, and risk (Khakpour et al., 2021); and iii) a coordination layer, with alerts, explanation of recommendations, filters, and a decision log (Nadj et al., 2020; Simkute et al., 2021).

The design prioritized visual hierarchy, correspondence between data and graphic channels, and the reduction of unnecessary elements (Franconeri et al., 2021). The flow was: data and events → visual encoding → analytical interface → operational decision. The backend was regarded as infrastructure; the analysis focused on the visual representation.

Figure 2. Flow of translation of operational data into a visually assisted decision.



Source: Authors' own elaboration.

3.5. Phase 4: Expert assessment of conceptual relevance and acceptance and illustrative comparative scenario.

The fourth phase comprised two complementary procedures: an expert assessment of conceptual relevance and acceptance, and an illustrative comparative scenario (Maldonado-Suárez & Santoyo-Telles, 2024). The two procedures examined different aspects of the proposal, and their results were not interpreted as equivalent evidence**.**

Ten experts took part in the assessment, purposively selected on the basis of their professional experience and their knowledge in the areas of logistics, transport, operational safety, and applied technologies. No uniform record of years of experience or common minimum quantitative threshold was available for all the experts; the selection is therefore reported as purposive, and this condition is acknowledged as a limitation of this phase. The assessment was carried out in a single round and considered four criteria: the need to implement a collaborative platform, the expected contribution to risk management, the importance of integrating artificial intelligence, and the acceptance of intelligent platforms.

Each criterion was rated on a 5-level ordinal scale: 1 = very low, 2 = low, 3 = medium, 4 = high, and 5 = very high.

For the descriptive analysis, the categories high and very high were considered favorable, and frequencies and percentages were calculated. This phase was interpreted exclusively as an assessment of conceptual relevance and acceptance, not as formal validation, usability testing, or an evaluation of operational effectiveness, since there was no interaction with a functional prototype and no measurement of times, errors, effectiveness, or satisfaction.

An illustrative comparative scenario was developed between UPSE, La Libertad, and San José, Santa Elena (Asghari & Mirzapour Al-e-hashem, 2021; Ghoul et al., 2023). A reference route was compared with a proposed route, keeping the same origin and destination; their geometry and duration were obtained using OSRM (Luxen & Vetter, 2011) . The comparison was descriptive and did not seek to demonstrate the superiority of an algorithm.

Measured consumption was 18 L in the reference scenario and 13 L in the proposed scenario; these values were used to estimate CO_2 emissions and do not come from OSRM. The scenario was illustrative and not experimental. The available documentation does not make it possible to reconstruct vehicle, load, distance, traffic conditions, or repetitions in a uniform way; the values are therefore interpreted solely within the scenario analyzed and not as generalizable evidence.

Operational risk was assessed using a matrix of probability (P) and consequence (C), both rated from 1 to 5, calculating NR = P × C. The scores were assigned by the research team according to the conditions and

controls of the scenario and do not derive from historical accident records. Risk levels (NR) were classified as low (1–4), medium (5–9), high (10–16), and critical (17–25).

The proposed scenario incorporated controls for safe driving, route and schedule planning, weather checks, selection of safe routes, road inspection, vehicle maintenance, and idling reduction. The change in risk therefore reflects the route, the assumptions, and the controls incorporated taken together, and cannot be attributed exclusively to the interface or interpreted as an empirical reduction in risk.

Under the assumptions defined, the reference scenario presented NR = 12–16 (high) and the proposed scenario NR = 6–8 (medium). This change is ordinal and does not represent an actual reduction observed under operating conditions.

The indicators compared were travel time, fuel consumption, estimated CO_2 emissions, and operational risk. The relative difference was calculated as:

$$\text{Relative difference (\%)} = [(\text{reference value} - \text{proposed value}) / \text{reference value}] \times 100.$$

Estimated CO_2 emissions were calculated using the expression $CO_2 = CC \times FE$, where CC is the total fuel consumption of the scenario, expressed in liters (L), and FE is the diesel emission factor, expressed in kg CO_2/L. For the comparison, the official factor of 2.681 kg CO_2/L reported by Environment and Climate Change Canada (2025) was adopted; for the calculations, the value rounded to 2.68 kg CO_2/L was used. This factor was used exclusively as a constant coefficient in the comparative estimate between the two scenarios and is not interpreted as a national emission factor specific to Ecuador. The comparative scenario was limited to a single comparison and was used for descriptive purposes. Consequently, the differences obtained are not interpreted as causal evidence of the effectiveness of the interface or as results that can be generalized to transport operations as a whole in the territory studied.

3.6. Analysis and ethical considerations

The data were analyzed using frequencies, percentages, and descriptive comparisons (Cooksey, 2020). No population inferences were made, owing to the non-probabilistic sampling; nor were causal inferences drawn from the illustrative comparative scenario, which delimits the scope of the results (Andrade, 2021). Participation in the research was voluntary. The original forms included participants' contact information; however, these data were not incorporated into the analysis or the presentation of results, which were processed and reported in aggregate form. The information obtained was used exclusively for academic and scientific purposes, preserving the confidentiality of the data collected.

After data collection, the Institutional Ethics Committee of the Universidad Estatal Península de Santa Elena issued a favorable opinion on the ethical considerations of the research. The Committee determined that the methodological design conforms to institutional ethical principles and to the international standards applicable to research involving human subjects, and acknowledged the voluntary nature of participation and the confidentiality of the information collected. The favorable opinion is recorded in Resolution No. 015-CE-UPSE-2026, dated August 24, 2026.

4. Results

The results are presented in accordance with the methodological sequence of the study: documentary context, needs diagnosis, proposed visual architecture, expert assessment, and illustrative comparative scenario. This organization makes it possible to answer the research questions separately without equating evidence from perception, design, expert assessment, and descriptive comparison.

4.1. Scientific context 2020–2025

The documentary sample consisted of 41 articles published between 2020 and 2025. The highest concentration was recorded in 2025, with 26 publications (63.4%). The review made it possible to contextualize the convergence between intelligent systems, transport, geospatial visualization, and decision support. These results are interpreted descriptively and not as evidence of the effectiveness of the proposed platform.

Table 1. Annual distribution of the documentary sample (2020–2025).

Year	Documents	Percentage (%)
2020	1	2.4
2021	3	7.3
2022	4	9.8
2023	5	12.2
2024	2	4.9
2025	26	63.4
Total	41	100.0

Source: Authors' own elaboration based on records retrieved from Scopus and Web of Science.

The concentration of publications in 2025, which accounts for 26 of the 41 documents analyzed (63.4%), should be interpreted with caution. This pattern may be related both to a recent increase in scientific interest in the convergence between intelligent transport systems, operational safety, digital platforms, and geospatial visualization and to the sensitivity of the search strategy to terminology recently incorporated into the literature. Consequently, this temporal distribution is used solely as an element for contextualizing the documentary sample and not as sufficient evidence to assert, by itself, an abrupt transformation or exponential growth of the scientific field.

4.2. Perceived visual and operational needs

The survey of 50 participants identified needs related to operational efficiency, monitoring, safety, and digital tools. One questionnaire had missing data for the ten items on logistics efficiency and operational safety; these dimensions were therefore analyzed with 49 valid cases, without imputation. The remaining dimensions retained 50 valid responses.

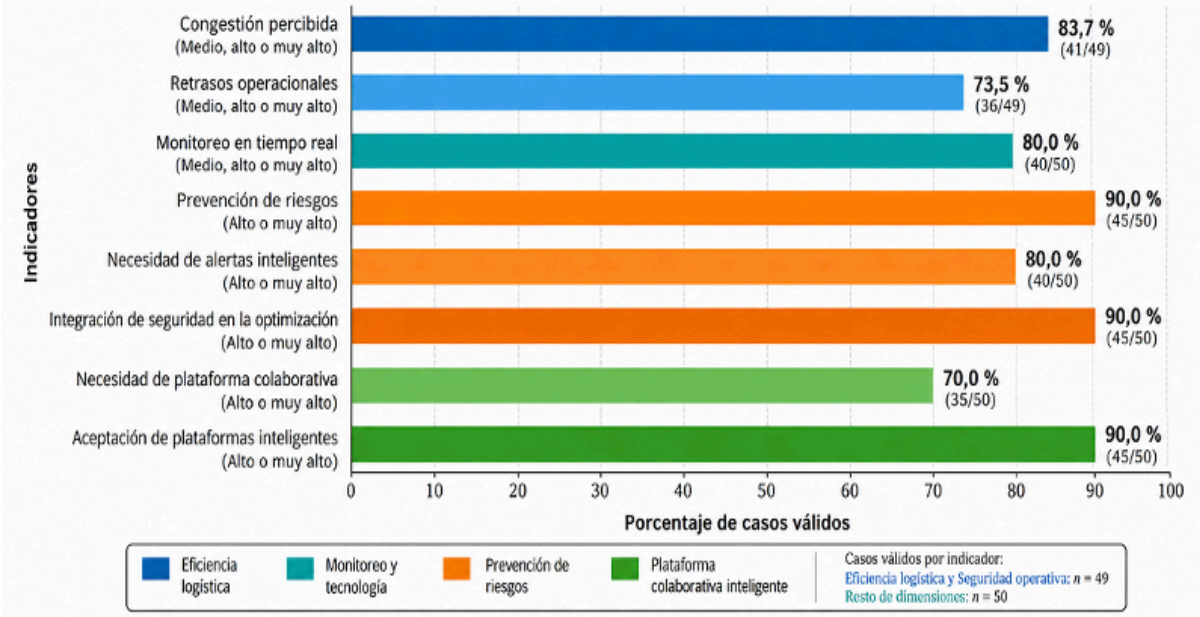
In logistics efficiency, 41 of 49 valid cases (83.7%) placed traffic congestion at medium, high, or very high levels, while 36 of 49 valid cases (73.5%) placed the frequency of delays in those same categories. In the monitoring and technology dimension, 40 of 50 participants (80%) rated real-time monitoring capacity as medium, high, or very high.

With regard to risk prevention, 45 of 50 participants (90%) gave a high or very high rating to the importance of implementing prevention systems, and the same proportion rated the integration of operational safety into route optimization favorably. The need for real-time intelligent alerts received 40 favorable responses out of 50 (80%).

As for the intelligent collaborative platform dimension, 35 of 50 participants (70%) gave a high or very high rating to the need to implement a collaborative logistics platform. Likewise, 45 of 50 (90%) expressed high or very high acceptance of the use of intelligent platforms in road transport.

Taken together, the results reveal needs related to the spatial representation of operations, real-time monitoring, risk prevention, the generation of alerts, and the integration of information into a collaborative interface. These findings were used as input for defining the information hierarchy and the components of the proposed visual architecture. Owing to the non-probabilistic and local nature of the sample, the results are interpreted as descriptive evidence concerning the participants studied and not as estimates generalizable to the population.

Figure 3. Selected indicators from the diagnosis of visual and operational needs (valid cases per indicator: n = 49–50).



Source: Authors' own elaboration based on the survey forms.

Table 2. Selected indicators for the diagnosis of visual and operational needs.

Indicator	Aggregated criterion	Cases meeting the criterion	Valid cases	%
Perceived congestion	Medium, high, or very	41	49	83.7
Operational delays	Medium, high, or very	36	49	73.5
Real-time monitoring	Medium, high, or very	40	50	80.0
Risk prevention	High or very high	45	50	90.0
Need for intelligent alerts	High or very high	40	50	80.0
Integration of safety into optimization	High or very high	45	50	90.0
Need for a collaborative platform	High or very high	35	50	70.0
Acceptance of intelligent platforms	High or very high	45	50	90.0

Source: Authors' own elaboration based on the survey forms.

The diagnosis showed that risk management and intelligent tools were highly valued. In total, 90.0% gave high or very high ratings to risk prevention, the integration of safety into route optimization, and the acceptance of intelligent platforms; 80.0% valued real-time monitoring and intelligent alerts. In addition, 83.7% perceived congestion as medium, high, or very high. These results were used as input for defining the proposed visual architecture.

4.3. Proposed visual architecture

On the basis of the diagnosis, a visual architecture was defined that is organized around an operational map, accompanied by indicators of travel time, fuel consumption, estimated CO_2 emissions, and level of operational risk. The map differentiates the reference route from the proposed route, represents the origin and destination, and incorporates risk-related elements.

Figure 4. Visual flow of the architecture.



Source: Authors' own elaboration.

The figure shows the sequence by which operational data are processed, transformed into cartographic and analytical information, and presented to the user to support operational decision-making.

The proposal is organized around an operational map, which is the central element of the screen. It represents the reference route and the proposed route using differentiated lines, together with the points of origin and destination, the logistics points, and the corresponding legend.

Risk encoding was structured in four levels: critical, high, medium, and low, combining color, text, and icons so that interpretation would not depend exclusively on color. The key performance indicators (KPIs) show the values for the reference scenario and the proposed scenario, while alerts are prioritized according to their level of severity. The proposal also incorporates contextual information to facilitate the interpretation of the factors associated with the recommendation of a route. This structure seeks to integrate geospatial information, operational indicators, and risk signals into a single representation, aimed at fostering a shared operational picture among logistics actors. However, the study did not evaluate, through interaction tasks, whether such a shared picture is actually constructed among users.

Table 3. Components of the visual information architecture.

Component	Function	Design criterion
Operational map	Represent logistics points, routes, and risk zones.	Cartographic clarity, visual differentiation of routes, and visible legend.
Comparative KPIs	Show travel time and fuel consumption.	Values, units, and reference clearly identified.
Environmental KPI	Show estimated CO_2 emissions.	Value and variation with respect to the reference scenario.
Comparison of alternatives	Contrast the reference scenario and the proposed scenario.	Joint presentation of values and percentage variation.
Risk encoding	Identify levels of operational risk.	Color, icon, and text label (critical, high, medium, and low).
Operational alerts	Communicate relevant events.	Severity, description, and suggested action.
Interaction controls	Facilitate the review and comparison of routes.	Filters, layers, date, selection of alternative, and export.

Source*:* Authors' own elaboration based on study data.

The conceptual mockup presented in Figure 5 was built from these components.

Figure 5. Conceptual mockup of the cartographic and analytical interface.



Source: Authors' own elaboration. Data and visual elements from the experimental comparative scenario, for design purposes.

Figure 5 shows the integration of the map, the performance indicators, and the prioritized alerts in the conceptual mockup.

4.4. Relevance and acceptance of the proposal

The assessment by 10 experts yielded favorable results: the need to implement a collaborative platform, its expected contribution to risk management, and the acceptance of intelligent platforms reached 90%, while the importance attributed to the integration of artificial intelligence reached 80% (Maldonado-Suárez & Santoyo-Telles, 2024).

Table 4. Expert assessment of relevance and acceptance (n = 10).

Criterion assessed	High/very high responses	Favorable assessment (%)
Need to implement the collaborative platform	9/10	90
Expected contribution to risk management	9/10	90
Importance of integrating artificial intelligence	8/10	80
Acceptance of intelligent platforms	9/10	90

Source*:* Authors' own elaboration based on study data.

The results support the conceptual relevance and acceptance of the proposal, but do not constitute evidence of usability, operational effectiveness, or an actual reduction in risk.

4.5. Results of the illustrative comparative scenario

The illustrative comparative scenario made it possible to contrast a reference route with a proposed alternative route using indicators of travel time, fuel consumption, estimated CO_2 emissions, and level of operational risk. The analysis was descriptive in nature and did not constitute a causal evaluation of the effectiveness of the interface.

The geometry and duration of the routes corresponding to the reference scenario and the proposed scenario were obtained with OSRM, keeping the same origin (UPSE, La Libertad) and the same destination (San José).

In the reference scenario, the estimated travel time was 95 min and, in the proposed scenario, 72 min, which represents a relative difference of 24.2%. Recorded fuel consumption decreased from 18 L in the reference scenario to 13 L in the proposed scenario, equivalent to a variation of 27.8%.

Estimated CO_2 emissions were calculated from total fuel consumption using the expression $CO_2 = CC \times FE$, where CC is the total fuel consumption of the scenario, expressed in liters (L), and FE is the diesel emission factor, expressed in kg CO_2/L. For the comparison, the official factor of 2.681 kg CO_2/L reported by Environment and Climate Change Canada (2025) was adopted. This factor was used exclusively as a constant coefficient for the comparative estimate between the two scenarios and should not be interpreted as a national emission factor specific to Ecuador.

Consequently, the values obtained represent comparative estimates for the scenario analyzed and do not constitute a local emissions inventory. Using the factor employed in the calculation, 48.24 kg of CO_2 were estimated for the reference scenario and 34.84 kg of CO_2 for the proposed scenario, which represents a variation of 27.8%.

Table 5. Comparison of the risk level between the reference scenario and the proposed scenario.

Variable	Reference NR	Reference level	Proposed NR	Proposed level
Accidents	15	High	8	Medium
Traffic	12	High	6	Medium
Weather	12	High	6	Medium
Insecurity	15	High	8	Medium
Road condition	16	High	8	Medium
Fuel consumption	12	High	6	Medium
Diesel-related emissions	12	High	6	Medium

Source*: Authors' own elaboration based on data from* the illustrative comparative scenario.

The risk matrix classified the reference scenario as high (NR = 12–16) and the proposed scenario as medium (NR = 6–8), under the conditions and controls defined. The change is interpreted ordinally and exclusively within the illustrative scenario, not as evidence of an actual reduction in operational risk.

Figure 6. Comparison of indicators between the reference scenario and the proposed scenario.



Source: *Authors' own elaboration. Data from* the simulated scenario.

The differences correspond to a single scenario and cannot be attributed exclusively to the interface or generalized to transport operations in Santa Elena.

5. Discussion

The findings show that the logistics problem analyzed goes beyond route calculation and includes the representation and interpretation of operational, geospatial, and risk information. The needs identified in the sample, the high perception of congestion (83.7%), the importance attributed to risk prevention (90%), and the favorable acceptance of intelligent platforms (90%) justify exploring interfaces that bring these dimensions together, although the results must be interpreted within the exploratory and non-probabilistic nature of the diagnosis. The proposed architecture integrates an operational map, comparative indicators, alerts, and redundant risk encoding. This organization is consistent with studies showing that cartographic design and dynamic information can influence the search for and interpretation of spatial information (C.-F. Wu et al., 2022). Likewise, keeping indicators and contextual elements visible is intended to prevent the algorithmic recommendation from being presented as a "black box" disconnected from human decision-making (Nadj et al., 2020).

The expert assessment supports the conceptual relevance and acceptance of the architecture, but does not demonstrate usability or operational effectiveness. These properties will need to be evaluated through interaction with a functional prototype and metrics of effectiveness, efficiency, errors, and satisfaction.

The differences observed in the comparative scenario are consistent with planning approaches that incorporate environmental and safety variables alongside mobility criteria (Asghari & Mirzapour Al-e-hashem, 2021; Ghoul et al., 2023; Sohrabi et al., 2022). However, since they derive from a single scenario, they cannot be attributed exclusively to the interface or generalized to transport in Santa Elena.

The main contribution of the study is an architecture of visual translation that brings together cartography, operational indicators, risk signals, and context in a common representation. From the standpoint of visual culture, this interface functions as a sociotechnical artifact that prioritizes information by means of KPIs, alerts, iconography, and risk encoding, mediating between data, territory, and human decision-making (Herrmann & Pfeiffer, 2023; Manovich, 2020; Söderlund & Hansson, 2021). The effective construction of a shared operational picture will need to be verified subsequently through studies of interaction and coordination among users.

The main limitations are the non-probabilistic and local sampling, the absence of a formal usability evaluation, the conceptual nature of the expert assessment, and the use of a single comparative scenario. It therefore cannot be claimed that the architecture by itself reduces cognitive load, accident rates, or actual risk. Subsequent studies should evaluate functional prototypes through user tasks, usability and accessibility metrics, and comparisons with alternative interfaces.

6. Conclusions

The study made it possible to formulate a collaborative visual architecture that integrates cartographic representation, operational indicators, alerts, and risk encoding to support the interpretation of logistics information. The diagnosis guided its design, and the expert assessment showed a favorable perception of its conceptual relevance and acceptance. The illustrative comparative scenario showed differences in time, fuel, estimated emissions, and risk level; however, these results characterize only the scenario analyzed and do not demonstrate an operational improvement attributable to the interface.

The main contribution is an architecture of visual translation that connects geospatial data, analytical processing, and human decision-making. It is preliminary, exploratory, and propositional in nature; its usability, operational effectiveness, and superiority over other interfaces have therefore not yet been demonstrated. The next phase should implement a functional prototype and evaluate it with users using metrics of effectiveness, efficiency, errors, satisfaction, and accessibility, in addition to incorporating further scenarios.

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Appendix A. Content of the needs diagnosis instrument.

The diagnostic instrument consisted of 25 items organized into five dimensions. The response scale was: 1 = very low, 2 = low, 3 = medium, 4 = high, and 5 = very high. The appendix reproduces the preserved content of the instrument used in the study.

Encuesta sobre optimización de rutas logísticas, seguridad operativa y prevención de riesgos en el transporte terrestre

Tema: "Diseño de una plataforma colaborativa para optimizar rutas logísticas que integre la seguridad operativa y la prevención de riesgos en el transporte".

Objetivo: Recopilar información sobre operaciones logísticas, seguridad operativa, monitoreo de rutas y prevención de riesgos en el transporte terrestre de la provincia de Santa Elena, Ecuador.

INSTRUCCIONES

Marque con una (X) el nivel que considere adecuado según su experiencia en operaciones de transporte terrestre.

Valor	Escala Likert
1	Muy bajo
2	Bajo
3	Medio
4	Alto
5	Muy alto

SECCIÓN I. EFICIENCIA LOGÍSTICA

N°	Ítem	1	2	3	4	5
1	Nivel de congestión vehicular en las rutas logísticas	□	□	□	□	□
2	Frecuencia de retrasos durante el transporte	□	□	□	□	□
3	Eficiencia actual de las rutas terrestres	□	□	□	□	□
4	Nivel de optimización de tiempos de recorrido	□	□	□	□	□
5	Nivel de consumo de combustible durante las operaciones logísticas	□	□	□	□	□

SECCIÓN II. SEGURIDAD OPERATIVA

N°	Ítem	1	2	3	4	5
6	Nivel de seguridad operativa en las rutas terrestres	□	□	□	□	□
7	Frecuencia de accidentes o incidentes operacionales	□	□	□	□	□
8	Nivel de riesgo asociado al estado de las vías	□	□	□	□	□
9	Impacto de las condiciones climáticas sobre las operaciones logísticas	□	□	□	□	□
10	Nivel de exposición a riesgos durante el transporte terrestre	□	□	□	□	□

SECCIÓN III. MONITOREO Y TECNOLOGÍA

N°	Ítem	1	2	3	4	5
11	Nivel de utilización de GPS para monitoreo de rutas	□	□	□	□	□
12	Nivel de digitalización de los procesos logísticos	□	□	□	□	□
13	Capacidad de monitoreo en tiempo real de las operaciones	□	□	□	□	□
14	Nivel de comunicación entre operadores logísticos y conductores	□	□	□	□	□
15	Nivel de uso de tecnologías inteligentes en el transporte	□	□	□	□	□

SECCIÓN IV. PREVENCIÓN DE RIESGOS

N°	Ítem	1	2	3	4	5
16	Importancia de implementar sistemas de prevención de riesgos	□	□	□	□	□
17	Capacidad actual para prevenir accidentes en rutas logísticas	□	□	□	□	□
18	Nivel de preparación ante emergencias operacionales	□	□	□	□	□
19	Necesidad de alertas inteligentes en tiempo real	□	□	□	□	□
20	Importancia de integrar seguridad operativa en la optimización de rutas	□	□	□	□	□

SECCIÓN V. PLATAFORMA COLABORATIVA INTELIGENTE

N°	Ítem	1	2	3	4	5
21	Necesidad de implementar una plataforma colaborativa logística	□	□	□	□	□
22	Impacto esperado de la plataforma sobre la eficiencia logística	□	□	□	□	□
23	Impacto esperado en la reducción de riesgos operacionales	□	□	□	□	□
24	Importancia de integrar inteligencia artificial en rutas logísticas	□	□	□	□	□
25	Nivel de aceptación del uso de plataformas inteligentes en el transporte terrestre	□	□	□	□	□

Firma encuestado _____

Nota: Lugares recomendados en Santa Elena: empresas de transporte, terminales terrestres, centros logísticos, distribuidoras, zonas industriales, cooperativas de transporte, empresas comerciales.

La población objetivo estuvo conformada por conductores, operadores logísticos y supervisores de transporte terrestre de la provincia de Santa Elena, Ecuador, debido a su participación directa en las operaciones de distribución, el monitoreo de rutas y la gestión logística.

Source: Original study instrument, retrieved from the preserved methodological record.