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Implications of technological changes in vehicle routing interfaces for planners' constraint processing

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Abstract

This study sought to assess the consequences of technological changes in vehicle routing interfaces for planners' constraint processing during route selection. We began by developing a model of domain constraints for the generic vehicle routing problem, in order to characterize planners' constraint processing and assess the visibility of constraints on different routing interfaces. An experiment featuring vehicle routing problems was then designed to test interfaces reflecting technological changes, including automation leading to simplified interfaces and the display of multiple routes computed by algorithms. Twelve participants who had worked for a small transport company for nine months were exposed to all these interfaces. Mental workload, performance and decision-making times were measured. Results revealed that automation decreases mental workload and decision times, attributable to the abridged (vs. unabridged) display of constraints on the interface. Results also showed that the perceptual (vs. analytical) display of routes greatly decreases decision times and enhances performances.

Keywords: vehicle routing, automation, decision support, planning, interface, domain, constraints, intentional systems.

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1. Introduction

The vehicle routing problem (VRP) embraces a class of complex problems consisting in determining an optimum route (chiefly by minimizing the total journey cost) for a set of customers who are subject to side constraints such as time windows and vehicle capacity. The VRP applies to the situation faced by postal organizations, which have to route a fleet of vehicles based in multiple depots to a set of customers with specific time windows for delivery (e.g., Hollis, Forbes, & Douglas, 2006). It also refers to intra-city transport companies providing *dial-a-ride* services using a heterogeneous fleet (e.g., minibuses) when booking is done either in advance or in real time (e.g., Rahimi & Dessouky, 2001).

In field studies, planners appear to play a crucial role, taking the large set of constraints into account and adapting to changes in the domain (Jackson et al., 2004; Sanderson, 1989). At the same time, the integration of transportation technologies is gradually changing the nature of these decision-making processes, in that vehicle routing interfaces now combine human planners and technologies. For instance, the introduction of global positioning systems (GPS), electronic data interchange (EDI) and geographic information systems (GIS) means that planners can now monitor vehicles more easily, on computer-based road maps. Then there are 'intelligent' transportation systems, which are designed to support decisions by means of powerful algorithms (Crainic, Gendreau, & Potvin, 2009). These new technologies are changing the way that routes are planned. More specifically, transport companies are shifting their focus away from stand-alone planners to planners supported by multiple technological systems.

We believe that these technological changes have at least two implications for routing interfaces and the allocation of routing tasks to vehicle planners. (1) The handling of the routing problem's physical constraints (e.g., computing distances between depots and vehicles) is now fully automated, leaving planners to concentrate on the functional aspects of the problem instead. However, if the interface only displays the problem's functional constraints, this can lead to poorer performances whenever the planner is called upon to handle a physical constraint that is not processed by the automated system (Couclelis, 2003). (2) Algorithms now generate multiple solutions, and in state-of-the-art interfaces, planners are allocated the task of selecting the most relevant one. This approach has long been criticized in industrial planning because it involves examining all the solutions in turn, which creates a very high workload (Sanderson, 1989; Schakel, 1976). This is certainly not without consequences for vehicle routing interfaces.

The present paper seeks to address these two significant implications of technological changes in terms of mental workload, performance and time taken to make decisions. We focus on the routing problem (i.e., selection of an initial solution), where the interface plays an important role, rather than on the real-time re-planning of vehicles, which tends to revolve around communication with drivers (Ng et al., 1995). We begin by discussing constraint processing and the importance of modeling the work domain in order to assess planners' constraint processing. We then describe an experiment that was designed to assess the implications of technological changes for routing. More specifically, we compared an interface providing all the constraints (both physical and functional; "unabridged") with an interface focusing solely on high-level constraints (functional constraints only; "abridged"). We then compared two interfaces allowing for the successive comparison of solutions (analytical processing of constraints) with a third interface enabling users to compare all the solutions at the same time (perceptual processing). Finally, we discuss the importance of taking planners' constraint processing into account when introducing technological changes.

2. Domain constraints in vehicle routing problems

2.1. PLANNERS' CONSTRAINT PROCESSING IN ROUTE SELECTION

Transportation technologies are rapidly moving toward greater automation. At one extreme, decisions related to route selection have now become fully automated. Taxi dispatching is a typical example of such a system. In taxi dispatching, a group of call-takers answer incoming calls and enter customers' locations into a database. A routing algorithm automatically selects the most appropriate vehicle according to different sets of constraints (available capacity, driver's work schedule, distance from the pickup point, and so on). Optimization criteria are well known and usually consist in minimizing time and distance to the pickup point. The taxi driver then receives a notification and either accepts or declines to pick up the customer.

In most routing situations, however, such fully automated systems are still uncommon because the optimum solutions cannot be determined with any degree of efficiency through automation alone (Lenior et al., 2006). In goods delivery, for instance, optimization criteria are particularly complex and planners are known to consider various unstated constraints: personal (e.g., how well the driver knows a particular route or foreign language), environmental (e.g., impact of weather conditions, traffic congestion), social (e.g., period of absenteeism), infrastructure (e.g., vehicle maintenance), and so on. The planner has a list of demands and has to prepare a sheet for each driver, on the basis of constraints such as locations, sequences, travel times and time windows for deliveries. This solution, which is also based on optimization criteria, is then given to each driver at the start of his or her shift. In an ideal world, the planner would design a route considering each constraint as an independent subproblem. However, as these constraints interact, planners cannot define an acceptable route without paying considerable attention to their interactions. In line with Stefik

(1981), we regard constraints as expressions of partial relationships among variables. They also partially specify the overall solution (route). Planners play a crucial role, taking the large set of routing constraints into account and adapting to changes in the problem constraints (Jackson et al., 2004; Sanderson, 1989). They also make a decisive contribution when problems are over-constrained, as their extensive knowledge allows them to relax constraints in order to arrive at an efficient solution (Gacias, 2010; Higgins, 1996, 2001; MacCarthy & Wilson, 2001). Planners play such a vital part in routing that full automation of route selection is impossible. If they are to be properly supported, it is important to identity all the constraints they have to process in order to design appropriate routing interfaces.

There have been a number of attempts to define the vehicle routing task structure on the basis of hierarchical task analysis (Rahimi & Dessouky, 2001) and cognitive task analysis (Wong & Blandford, 2002). However, when Cegarra and van Wezel (2010) compared the amount of information produced by these two methods, as well as by work domain analysis, they found that the latter was far more exhaustive in identifying constraints, not least because it provides a generic view of constraints and does not focus on usual or known tasks. Work domain analysis (WDA) was developed by Rasmussen and colleagues (Rasmussen, Pejtersen, & Goodstein, 1994; Vicente, 1999) and emphasizes on the domain constraints. Initially, it was applied to “causal” systems guided by physical laws, as in nuclear power stations (Itoh, Sakuma, & Monta, 1995), conventional power stations (Burns, 2000) and cement milling plants (Van Paassen, 1995). In “causal” systems, the objective reality is imposed on the human operator (Vicente, 1999), as opposed to “intentional” systems, where the operator is the main agent of the domain and there are fewer references to an external environment. This is the case of routing problems, where it is difficult to enumerate the constraints in a generic fashion because they result partly from conventions, organizational objectives, formal or informal rules and operators’ goals.

2.2. TOWARD COMPLETENESS OF DOMAIN CONSTRAINTS

At the lowest levels of the routing constraint space, we find physical objects such as vehicles, goods, drivers or depots. These objects are easily identified through interviews or observations. The highest levels, however, may well include human activities, for which work domain analysis is inappropriate. For instance, when Wong, Sallis, and O'Hare (1998) produced a tentative breakdown of ambulance dispatching, they initially conducted a cognitive task analysis and then used their findings to model the work domain. The authors included human tasks in their breakdown (e.g., "Locate nearest available ambulance", "Dispatch in 3 minutes"), meaning that the analysis did not focus solely on domain constraints. Hajdukiewicz, Burns, Vicente, and Eggleston (1999) criticized this approach and undertook a different breakdown, trying to describe the constraints more independently of the decision-maker (see Fig. 1). At the top of their hierarchy is the overall *functional purpose* of the system, namely taking care of sick or injured people based on acceptable risks and resource constraints. This is done by prioritizing emergencies according to several *abstract functions*: 'survival/damage' (degree of urgency), 'resource balance', 'time' and 'probability of successful treatment' (related to transportation and care quality). Moving down to the lower levels, the description focuses increasingly on the physical aspects, such as *physical functions*: capabilities and limitations of resources to handle emergencies (e.g., ambulance speed, vehicle only offering first aid). Finally, *physical form* describes the appearance, condition and location of the emergencies.

INSERT FIGURE 1 ABOUT HERE

Even so, when we look carefully at their proposed breakdown, we see that it is based on a hypothetical situation featuring two available ambulances and two emergencies (see Fig. 1). Vicente (1999) stressed that work domain analysis should be performed independently of usual or known tasks, the aim being to provide an exhaustive breakdown that is resistant to changes in the situation. Thus, while their breakdown focuses on constraints, not planners' tasks, it still deals with known cases, which is not compatible with the idea of a detailed and resilient view of constraints. In view of this, we sought to enhance the identification of domain constraints by extending the scope of the domain. More specifically, instead of focusing on currently known or usual cases in one particular situation (which inevitably leads to the inclusion of more details about the current situation), we set out to identify constraints by looking at different situations documented in the literature. Each variant of the VRP would allow us to increase the completeness of the constraint space by considering constraints which might potentially help to identify planners' degrees of freedom. Our search for VRPs in scientific databases yielded more than ten thousand articles. However, only a few of them suggested genuinely new variants of the generic VRP (see Toth & Vigo, 2002). Instead, researchers tended to develop algorithms to solve known variants or design algorithms for multiple variants (e.g., Pisinger & Ropke, 2007). The variants extended the domain by providing constraints related to a temporal perspective, including customers' time windows (VRPTW) and vehicles with limited capacity (CVRP), as well as more complex ones, such as trucks and trailers (TTRP), pick-up and delivery (VRPPD), or constraints related to multiple depots (MDVRP).

INSERT FIGURE 2 ABOUT HERE

As previously indicated, work domain analysis organizes the planners' constraint space in terms of different concepts that planners can then use for reasoning within a work system. We believe that the classic five levels of the abstraction hierarchy are needed to describe this space, as exemplified in Figure 2. Detailing each level is beyond the scope of this article, but readers can refer to Gacias (2010) and Gacias, Cegarra, and Lopez (2010) for further details about the different variants and the procedure we used to achieve this model.

3. Challenges for constraint processing following technological changes

Harper et al. (1998) performed a task analysis of vehicle planners and noted that it was necessary both to improve positional information about vehicles for correct planning and to reduce tasks requiring the entry of large amounts of data. These recommendations have since been met by the introduction of technological changes, with companies increasingly integrating new systems such as GPS, EDI and GIS into their internal systems, and the development of support systems to aid in routing decisions and reduce time-consuming tasks. This brings us to the two main technological changes under consideration in our study.

3.1. AUTOMATION AND CONSTRAINT ABRIDGMENT

The introduction of new automation devices has brought about a major change in routing procedures. GPS help planners to gather information about vehicles' current routes and automatically compute journey times to customers. EDI systems, such as on-board computers, allow locations and other information to be automatically transferred between planners and drivers. GIS, meanwhile, are gradually being integrated with GPS and EDI, and allow planners to easily monitor vehicles on computer-based road maps. Keenan (1998) noted that planners can greatly improve the quality of routes produced by automated systems. Furthermore, because planners' decisions are partly based on positional information, he argued that routing interfaces should be supplemented with GIS technology.

However, with this increasing automation and the introduction of hardware devices, the work situation of planners will inevitably start to resemble supervisory control in process industries (Lenior et al., 2006). As such, to select routes, planners will no longer need to have extensive knowledge about physical constraints, especially spatial ones (e.g., location of vehicles or customers). In addition, with GPS and EDI automatically computing distances, planners will find it easier to combine these constraints with basic information about road networks. They will simply have to choose the most relevant solution according to optimization criteria such as the overall cost of the solution. If the physical levels of the abstraction hierarchy are automated, planners will naturally focus their attention on the functional levels (optimization criteria). Moreover, it is often recommended to design interfaces that favor direct perception of higher-level constraints (Vicente, 2002). In the present study, an interface showing only the functional constraints was referred to as “abridged” and an interface showing both physical and functional constraints was referred to as “unabridged”. We hypothesized that participants using an abridged interface rather than an unabridged one would require less time and mental workload to select routes and would perform better (Hypothesis 1).

3.2. DECISION SUPPORT AND ROUTE SELECTION

More recently, transportation systems have started to focus on software issues, especially the use of powerful algorithms to support decision-making (Crainic, Gendreau, & Potvin, 2009). Algorithms form the basis of ‘intelligent’ transportation systems and are based on either mathematical models (operational research; OR) or knowledge representation formalisms (artificial intelligence; AI). They are needed to deal with problem complexity and to supply complex data, for instance by anticipating peak demands (Linton & Johnston, 2000), or providing values for shift optimization (Taylor & Huxley, 1989). A second purpose of these algorithms is generally to reduce the time-consuming task of manually designing repetitive plans for the vehicle fleet (e.g., Avramovich, Cook, Langston, & Sutherland, 1982).

As previously noted, planners have to choose the most appropriate solution according to the current goal. To this end, powerful algorithms provide the capability to compute all the possible solutions. The planners are then shown all these possible solutions, displayed on a computer screen one at a time. However, this approach involving the analytical processing of solutions has long been criticized in industrial planning for generating a very high mental workload and sometimes leading to poor decision-making (Sanderson, 1989; Schakel, 1976). A real-world example is described by Mietus (1994), who noted that planners who were offered multiple solutions often finally focused on only one of them. Cegarra and Hoc (2008) demonstrated that planners sometimes accept a level of performance that is lower than the level they are capable of achieving, due to the very high mental workload of solution analysis.

According to Vicente (1999), interfaces should favor direct perception of visual patterns, as planners' powerful visual perception of patterns has frequently been noted (Dessouky et al., 1995; Sanderson, 1989; Trentesaux, Moray, & Tahon, 1998). Ormerod and Chronicle (1996), for instance, showed that visual perception allows planners to find close approximations to optimum solutions for simple routing problems at low computational costs. An effective approach to supporting decisions would thus consist in collating and integrating multiple routing solutions into a single visual form (see Bennett & Flach, 1992). This way, planners would be guided in their use of perceptual rather than analytical processing of the constraints. An interface displaying the solutions separately (requiring analytical processing) would therefore result in poorer performances, longer decision times and a higher mental workload than an interface presenting all the solutions simultaneously (and allowing for perceptual processing) (Hypothesis 2).

These two types of interfaces focus solely on functional constraints (both are "abridged interfaces") and require algorithms to produce adequate routes on the basis of information from GIS, EDI and GPS. However, there are always data that escape automation (Couclelis, 2003). For instance, congestion black spots are not always taken into account by automated systems, whereas this is precisely the kind of supplementary knowledge needed for route selection that human operators possess. When Golob and Regan (2003) conducted a survey of 700 trucking companies operating in California, 85% of managers said that traffic congestion caused missed schedules and 36% regarded congestion as a serious problem for their businesses. The interface should therefore display not just functional information but also information about crucial physical constraints (e.g., traffic status in a particular location), which is not the case in "abridged" interfaces. When the planner interacts with an "abridged" interface, we can thus deduce that solving a problem with a *physical* constraint will require more time and a higher mental workload, and result in poorer performances, than solving a similar problem with a *functional* constraint (Hypothesis 3)

4. Constraint processing: an empirical assessment

4.1. PARTICIPANTS

In most companies, routing problems are solved by just a single planner or a very small group of individuals. Moreover, due to the extreme diversity of routing situations, it is often difficult to generalize results (Cegarra, 2008). For this reason, most routing and scheduling experiments have been carried out with students. However, it can be difficult to reach conclusions about interface design, as students do not have the experience needed to solve routing problems. For this study, we therefore gave participants extensive training beforehand.

Twelve participants (mean age: 23.8; six men, six women) spent nine months working for a small firm of consultants who mainly provide fleet management analyses for the private and public sectors. More specifically, they carried out a variety of tasks related to transportation and routing. These included analyses of customers' sites in order to assess distribution costs, analyses of companies' transport costs (multiple transport modes), and fleet utilization assessments. In particular, they worked on a case in the same geographical area as the one used as the context for this study. At the end of these nine months, we deemed that they had all acquired sufficient experience of the transportation domain and reached approximately the same level of practice in transportation cost assessment and route selection.

4.2. EXPERIMENTAL DESIGN

The experiment used a 2 x 3 within-participants design. The independent variables were scenario type (physical vs. functional constraint) and interface (analytical + abridged vs. analytical + unabridged vs. perceptual + abridged). All six conditions required participants to select the best solution from a set of thirty computer-generated solutions.

Participants were individually invited to take part in the experiment. They were first given a document introducing them to the context of the routing problem. They then familiarized themselves with the three interfaces by using them to solve a number of training problems. This training phase was repeated until they had correctly solved all the problems. Participants were then administered one problem in each of the six conditions, in a pseudo-random order. Each time they embarked on a fresh problem, participants were instructed to find the least costly solution (performance criterion) that satisfied one particular constraint (either functional or physical). Unlike the training phase, no performance feedback was provided after the completion of each problem.

Each problem was designed in such a way as to produce thirty solutions, five of which satisfied the relevant constraint. One of the five was calculated using the classic Bellman-Ford algorithm (Bellman, 1958), which finds the shortest path in polynomial time with a minimum cost in a graph. The four others were all acceptable routes, but with different modes of transport and higher transportation costs. Therefore, the computational nature of each problem was the same, meaning that any significant difference in the variables we measured related solely to the experimental condition (scenario or interface).

4.3. CONTEXT AND SCENARIOS

A real-life problem of waste collection was taken as the context for this study. Each year, a producers' organization in the French department of Seine-et-Marne grows several hundred thousand tons of beet. Harvesting starts in July and ends in October, before surface temperatures fall below freezing. The beets are cleaned in order to remove sand, soil and stones. The sand is then either transported by the producers to an expensive waste collection site or sold at a low price to construction companies. Overall, the producers' organization has to plan the transportation of the sand with a view to minimizing the total costs (transportation costs and unloading costs for the unsold sand) and (a secondary concern) the number of days required for transportation. This context allowed us to design several problems.

INSERT FIGURE 3 ABOUT HERE

In our experiment, 4,550 tons of sand had to be routed from the producers' depot ("La Chapelle Rablais" in Fig. 3). The planner had to deliver as many tons as possible to construction companies ("Poincy", "St-Rémy-la-Vanne", "Rouilly", "Rozay-en-Brie" and "Episy" in Fig. 3) in order to minimize the quantity of sand that would have to be unloaded at the waste collection site ("Claye-Souilly"). Multiple constraints had to be taken into account.

First, unloading at the waste collection site cost about €100/ton, while the construction companies would take the sand for free and sometimes even pay a small amount of money for it (see Table 1). Furthermore, the waste collection site was large enough to take all the producer's sand, whereas the construction companies differed in the amount they could take, according to their construction needs.

INSERT TABLE 1 ABOUT HERE

Second, a number of different transportation modes were available: trucks, barges, and trains. For each mode of transport, capacity, transportation cost (cost/ton/km), and average speed constraints had to be considered (see Table 2). With road transport (trucks), the costs of traveling back and forth also had to be included. Two of the modes (barges and trains) were only possible from one fixed point to another, along fixed routes: the barge docks were located in “Dammarie-les-Lys” and “Meaux”, while there were train depots in “Melun”, “Nangis” and “Provins”.

INSERT TABLE 2 ABOUT HERE

The abstraction hierarchy presented in Figure 2 was used to determine the relevant physical and functional constraints in this waste collection context. It indicated that not all the constraints of the work domain analysis were needed to produce a solution.

The system’s functional purpose is twofold: find a solution that both minimizes costs and ensures adequate customer service. In our experiment, the company was both the planner and the customer of the solution, and the most important constraints therefore related to costs. Regarding the values and priority measures (second level of the hierarchy), the planner needed to consider global capacity first (total cost of transport), followed by the number of days needed to implement the solution. At the lowest level of the abstraction hierarchy, the planner needed to take into account the types of vehicles available, the volume that had to be routed, and the location of the depots. These constraints determined the number and type of vehicles needed to handle the volume, the routes they took, and their travel times (different speeds for different modes).

Before each condition of the experiment, participants were told that they would have to satisfy one of two types of constraints:

A high-level, functional constraint. This involved looking for solutions whereby all the sand could be routed in the space of a set number of days (e.g., “You have to determine the least costly route for dispatching the sand in less than 5 days”);

A low-level, physical constraint. Here, they had to avoid a particular route due to congestion (e.g., "You have to determine the least costly route for dispatching sand, avoiding the 'La Chapelle Rablais'-'Meaux' road due to extensive roadworks").

4.4. INTERFACES

We designed three different interfaces for selecting the solutions (see Fig. 4).

INSERT FIGURE 4 ABOUT HERE

The first interface (*a*) provided only functional information about the thirty solutions, which were displayed one at a time. The user had to click on arrows to browse through the solutions, which implied analytical processing of these solutions. Each screen consisted of performance measures (transportation cost, number of vehicles used, time required for the collection). As only functional information was shown on the screen, this was dubbed the "abridged interface". In this interface, physical constraints such as the route used by vehicles or the locations were not displayed.

The second (analytical) interface (*b*) had the same structure, but this time physical information was added to each solution. More specifically, a map was displayed, highlighting the routes used by the different modes of transport for a given solution. This allowed both the problem's physical and functional constraints to be visualized ("unabridged interface").

The third interface (*c*) was regarded as a 'perceptual' interface, in that it presented all the solutions simultaneously on the screen. Participants therefore did not need to browse through the solutions because they were all presented on the screen. Instead, they had to circle the selected solution with the mouse. Only functional information was provided on this (abridged) interface. It therefore differed from the first one not in the information being displayed but in the way the solutions were presented (simultaneously vs. successively).

For the purpose of our analyses, the first, abridged, interface (a) constituted the control condition.

4.5. PERFORMANCE MEASURES

In order to assess the participants' behavior and compare their performances in relation to the scenarios and the interfaces with which they had to interact, we selected three measures:

- Routing performance: This performance measure referred to the instructions given to participants, namely to minimize costs whilst satisfying the prescribed constraint. We deemed that the participant had successfully solved the problem if he or she selected the solution with the best performance.
- Time performance: unlike the measure of routing performance, time performance was a measure not of the outcome but of the cognitive process. Participants needed time to compare the solutions and select the most appropriate one. Longer times could be assumed to reflect more demanding cognitive processes.
- Mental workload: We reviewed various workload analysis methods in terms of their invasiveness and opted for measures that were directly obtained from participants. Accordingly, workload was assessed with the NASA-TLX (Hart & Staveland, 1988). The NASA-TLX is a multidimensional rating scale procedure. It probes six dimensions of workload: cognitive demand, physical demand, temporal demand, effort, performance, and frustration. It is often considered to be not only the most sensitive subjective measure, but also the most reliable one (Cegarra & Chevalier, 2008; Hill et al., 1992). The French-language version was validated prior to this study (Cegarra & Morgado, 2009).

4.6. RESULTS

In order to test statistical significance, we performed repeated-measures ANOVAs. We controlled the overall Type I error rate of the planned comparison by adjusting the *p* value downward for declaring statistical significance ($p = .0125$). Moreover, a priori power analyses performed with G*Power software (Faul, Erdfelder, Buchner, & Lang, 2009) showed that an optimum sample size would be $N = 52$. This was far higher than the number of available participants in our study and directly affected the probability of the Type II error-retaining a false null hypothesis. Because it would not have been possible to distinguish between the absence of an effect and the lack of statistical power needed to detect an effect, nonsignificant results were regarded as inconclusive and are not discussed here.

4.6.1. Abridged vs. unabridged interface

4.6.1.1. Time taken to select a solution

INSERT FIGURE 5 ABOUT HERE

The comparison of interfaces, illustrated in Figure 5, showed that the task took longer to perform with the unabridged interface than with the abridged one. There was therefore an overall significant effect of interface type across all the scenarios, $F(1, 11) = 27.212$, $p = .000$, $\eta_p^2 = .546$. In terms of behavioral performance, it took participants longer to make decisions when all the constraints were visible on the interface.

Concerning scenario type (physical vs. functional constraint), we failed to observe any clear difference in total times between the two interfaces and our statistical analyses failed to reveal any overall significant effect of scenario type across the interfaces, $F(1, 11) = .486$, $p = .493$, $\eta_p^2 = .021$.

4.6.1.2. Mental workload

INSERT FIGURE 6 ABOUT HERE

Concerning the effect of interface type (Fig. 6) we observed small but consistent differences in workload between the unabridged and abridged interfaces. Statistical analyses highlighted an overall significant difference between the two interfaces, $F(1, 11) = 11.317$,

$p = .003$, $\eta_p^2 = .330$. Thus, a smaller mental workload was involved in finding solutions with the abridged interface than with the unabridged one.

There was a comparable difference in workload according to type of constraint (Fig. 6). We were thus able to identify a significant overall effect of scenario, $F(1, 11) = 8.769$, $p = .007$, $\eta_p^2 = .276$. Participants experienced a higher workload when they considered physical versus functional constraints.

4.6.1.3. Routing performance

INSERT FIGURE 7 ABOUT HERE

Regarding the percentage of participants who successfully solved the problem, there was no clear difference between either the interfaces or the scenarios (Fig. 7). In every condition, two or three participants systematically failed to find the best solutions. A detailed scrutiny of the solutions they selected showed that these were almost always the second or third best. Only one participant selected a solution that did not satisfy the physical/functional constraint.

Using performance (success/failure) as a dichotomous variable raises concerns as to the applicability of analyses of variance. A variable taking the value of zero or one to count the number of correct answers is not normally distributed. Lunney (1970) argued that analyses of variances are robust for dichotomous variables if the response proportions are less extreme than 20%-80%. This was not, however, the case for these results. We therefore proceeded to conduct nonparametric chi-square tests. Results failed to reveal a significant effect of either interface [$\chi(1) = .000$, *ns*] or scenario [$\chi(1)=.000$, *ns*] on successful outcome.

In terms of behavioral performance, scores confirmed the fact that participants generally found the correct solution ($\geq$ 75% success).

4.6.2. Analytical vs. perceptual interface

4.6.2.1. Time taken to select a solution

INSERT FIGURE 8 ABOUT HERE

Looking at the results from a descriptive point of view, we observed that decisions took less time to make with the perceptual interface than with the analytical interface (Fig. 8). More specifically, results showed that there was an overall significant effect of interface type across all conditions, $F(1, 11) = 13.104$, $p = .001$, $\eta_p^2 =.363$, with participants making decisions faster with the perceptual interface than with the analytical ones.

Furthermore, there was an overall significant effect of type of scenario across the interfaces, $F(1, 11) = 36.109$, $p = .000$, $\eta_p^2 = .611$. This indicated that participants worked faster when they had to consider a functional constraint rather than a physical one.

4.6.2.2. Mental workload

INSERT FIGURE 9 ABOUT HERE

When we looked at mental workload, there did not appear to be any difference between the interfaces. Statistical analysis also showed that there was no significant overall effect of interface on mental workload, $F(1, 11) = .202$, $p = .657$, $\eta_p^2 = .009$. However, due to the small sample size, it was not possible to conclude as to the absence of effect or the lack of statistical power.

There appeared to be a small difference between the physical and functional constraint scenarios (Fig. 9). A descriptive analysis allowed us to determine that there was a greater mental workload for physical constraint scenarios than for functional constraint ones. This finding was strengthened by a statistical analysis, which revealed a significant effect of scenario on mental workload, $F(1, 11) = 19.125$, $p = .000$, $\eta_p^2 = .454$.

4.6.2.3. Routing performance

INSERT FIGURE 10 ABOUT HERE

During the experiment, virtually no errors were committed whilst using the perceptual interface (see Fig. 10). Only one of the participants using this interface missed the correct solution, relaxing the functional constraint that had been given. Two of the participants using the analytical interface failed to find the best solution with functional constraints and three of them failed to find the best solution with physical constraints. Chi-square tests did not reveal a significant effect of interface on performance [$\chi(1) = .381$, *ns*]. No significant effect was observed for scenario [$\chi(1) = .000$, *ns*]. Nonetheless, it is worth noting that only participants handling physical constraints with the perceptual interface achieved perfect route selection performances.

5. Discussion

5.1. ABRIDGED VS. UNABRIDGED INTERFACE

Results indicated that an abridged interface requires less time and mental workload to select a solution, all the while ensuring a high level of performance. More generally, our results confirmed our first hypothesis and showed that participants did not have to see the lower levels of the abstraction hierarchy to make decisions when these levels were only needed by the system (GPS, GIS, EDI) to calculate solutions. Keenan (1998) had previously argued that routing interfaces should be supplemented with maps and spatial data (e.g., administrative boundaries). However, our results indicated that this lower-level information was superfluous to requirements. In all probability, when an interface contains supplementary information about the solution, planners laboriously take all this excessive data into account, resulting in an increase in decision time and mental workload.

This does not mean to say that physical constraints such as spatial information are not crucial for resolving routing problems. If planners are in frequent communication with drivers during route execution, they are more likely to require route and navigation information to carry out real-time monitoring. Thus, planners who currently use GIS regard these features as important for communicating with drivers (Ng et al., 1995). This is mainly because they need to view the situation from the drivers' perspective. Accordingly, while computer-based maps are useful for supporting communication with drivers, we can conclude that they are of little assistance to experienced planners when they are selecting the initial routes.

A similar conclusion has been reached in the industrial scheduling domain. In this domain, the Gantt chart, which displays the use of resources on the y-axis and time on the x-axis, is the most popular way of representing solutions. For this reason, various authors have suggested that humans should be supported by Gantt charts (e.g., Adelsberger & Kanet, 1989; Kurbel & Ruppel, 1996). However, these charts have also been criticized, for helping humans to communicate the plan to other individuals but not necessarily to reach planning decisions (Higgins, 1996). Therefore, as Trenteseaux, Moray, and Tahon (1998) suggested in the industrial domain, and as demonstrated by our results, new graphical forms need to be developed for route selection.

5.2. ANALYTICAL VS. PERCEPTUAL INTERFACE

Results showed that an interface facilitating perceptual rather than analytical processing requires less time for decision-making. While the results on mental workload are inconclusive, the decision time finding partly confirms our second hypothesis. This result is also in line with other studies showing that planners who have to undertake pairwise comparisons are impacted in their decision-making (Sanderson, 1989). Similarly, there is now a large body of literature arguing for integrated rather than separate displays (Bennett &

Flach, 1992). Integrated displays collate and integrate data from multiple sources ("sensors") into a single visual form, unlike separate displays which map each source to a different display. Our results stress the importance of facilitating the perceptual processing of constraints in order to facilitate the decision process. A secondary benefit of having all the information available in computers is the possibility of sharing this information among the company's different departments (shipping, planning, drivers), thus facilitating the overall routing process (Scapinakis & Garrison, 1991).

Nonetheless, one limitation of our study relates to the reliability of the data. In our experiment, participants consistently performed well across all the conditions, selecting solutions that satisfied the prescribed constraints. Implicitly, the solutions were designed as though the computer had access to the physical constraint (traffic congestion) when it designed the routes. In practice, however, this constraint is not available to computers and they sometime generate solutions on the wrong basis. Moreover, unreliable data can considerably affect the performance and usefulness of integrated displays, as Reising and Sanderson (2004) demonstrated in their study of the Pasteurizer II microworld. This limitation highlights the need for a follow-up study of how planners react to imperfect solutions. For instance, Reddy et al. (1995) analyzed the route selection behavior of students using simplistic routing software. They noted that acceptance of the single solution proposed by the computer was related to its accuracy. More specifically, if they had been given poor advice, participants chose not follow the computer's advice for subsequent trips, although they did sometimes start following it again if the accuracy of the computer-generated routes increased. When they looked at experienced planners, Ng et al. (1995) found that they set little store by the route selection features of automated systems because they trusted in their own ability to find an appropriate route. These results are in line with research on trust and self-confidence (Lee & See, 2004) and highlight the need to explore the design of trustable routing systems, for instance on the basis of “sensor abstraction hierarchies” (Reising & Sanderson, 2004) to determine potential automation inadequacies and their consequences for routing interfaces.

Another important result of our study is the increase in workload and decision-making time for physical as opposed to functional constraints for both interfaces. At first sight, this would appear to confirm our third hypothesis. However, these results need to be set against performance, as the perceptual interface allowed participants to achieve perfect performance on physical constraint scenarios, which seems incompatible with our hypothesis. Moreover, in the comparison of abridged vs. unabridged interfaces, we noted that mental workload was higher for the physical constraint than for the functional one for both interfaces. Overall, these results emphasize that finding an adequate route with a physical (spatial) constraint is a demanding task even in the presence of a computer map. One possible explanation is that these maps are inadequate to support physical constraint processing.

Golob and Regan (2002) showed in a survey that planners regard computer maps as one of the least useful means of reporting traffic congestion. At the same time, they noted that traffic maps were deemed to be helpful for carriers with long load moves (>800 km) but not for private carriers (transporting only their own goods) and carriers with short load moves. This directly relates to previous experience of the road network. Planners who are not familiar with the road network (as is the case for long moves) probably need maps to visualize the routes, whereas well-informed planners (e.g., those repeating short moves) do not. For experienced planners, like our participants, alternative routes may not necessarily be best supported by maps, as these routes are already known to them. This idea is also supported by different investigations of planners’ practice, showing that information about traffic conditions is mainly obtained from radio reports and direct communication with drivers and is not necessarily based on maps (Hall & Intihar, 1997). This underscores the need to design innovative interfaces for visualizing spatial constraints in an efficient manner, rather than providing planners with information they already have in their heads. More generally, our listing of constraints in the form of an abstraction hierarchy (see Fig. 2) could serve in follow-up empirical studies to identify the constraints (time, capacity, etc.) that planners already handle well and those that really deserve to be supported.

6. Conclusion

There are many obstacles to the design of empirical studies in the routing domain. The presence of only a few planners in each company, the complexity of domain modeling and the interdisciplinary nature of these issues all make it difficult for researchers to analyze routing interfaces. This probably explains why the latest peer-reviewed article empirically assessing the perception of constraints in planning problems was published so long ago (Gibson & Laios, 1978). Since then, many authors have expressed concern at the dearth of empirical studies of planning/routing (Hoc, Mebarki, & Cegarra, 2004; Moray, Hiskes, Lee, & Muir, 1995; Sanderson, 1989).

Technological changes have implications for the way planners solve vehicle routing problems. Our results on route selection have direct consequences for the design of routing interfaces. More specifically, they validate the inclusion of automation and decision support in interfaces. However, they also stress the need to evaluate routing interfaces in terms of information reliance (abridgment), automation accuracy (trust) and graphical forms tailored to meet genuine support needs. At the end of the day, our results reinforce the idea that it is not the technology itself that is the key to its application in routing, but rather the way in which it is merged with planners' decision-making processes.

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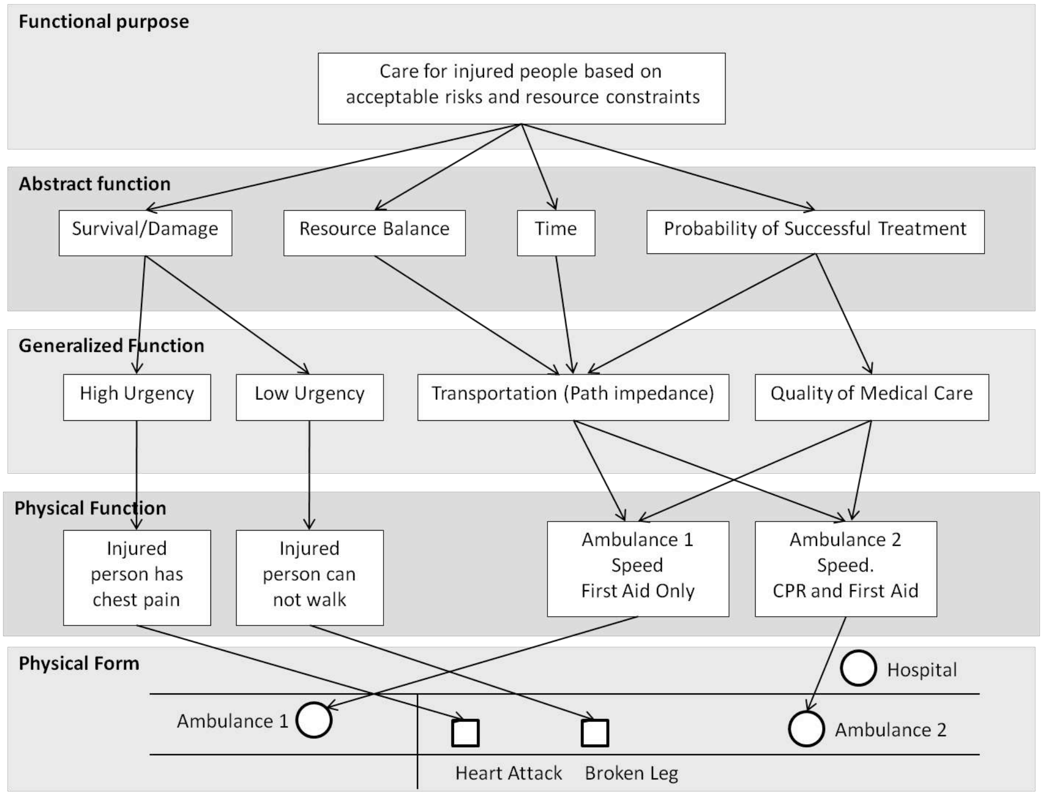


Figure 1. Breakdown of ambulance dispatch management (Hajdukiewiczk, Burns, Vicente, & Eggleston, 1999).

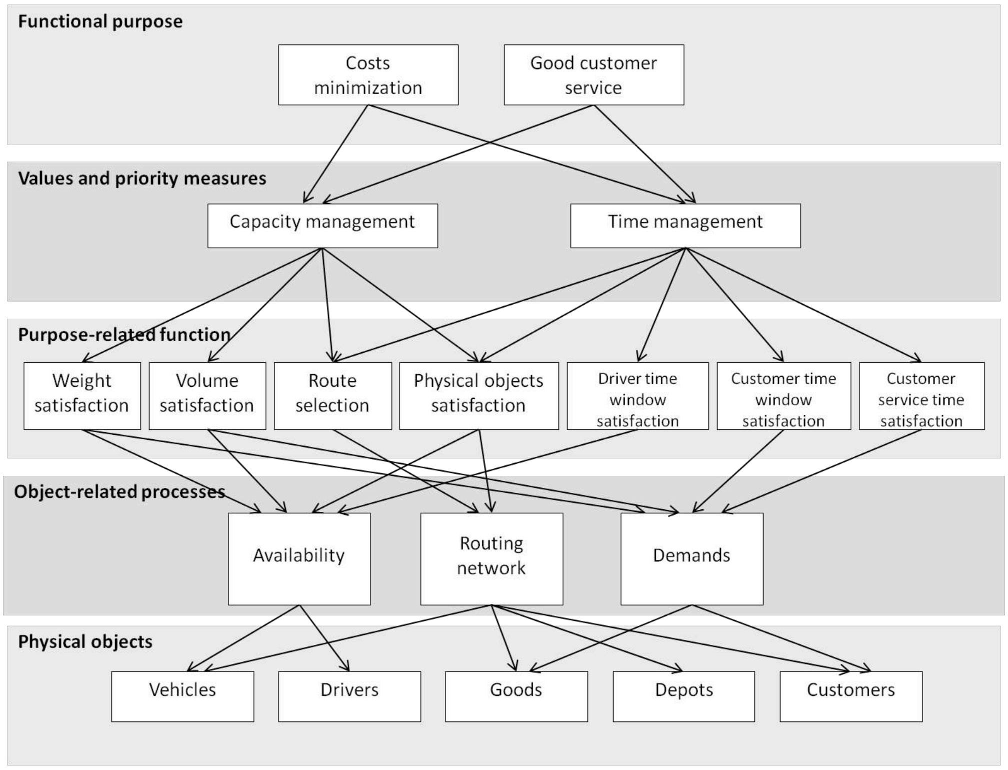


Figure 2. Work domain analysis of the generic vehicle routing problem.

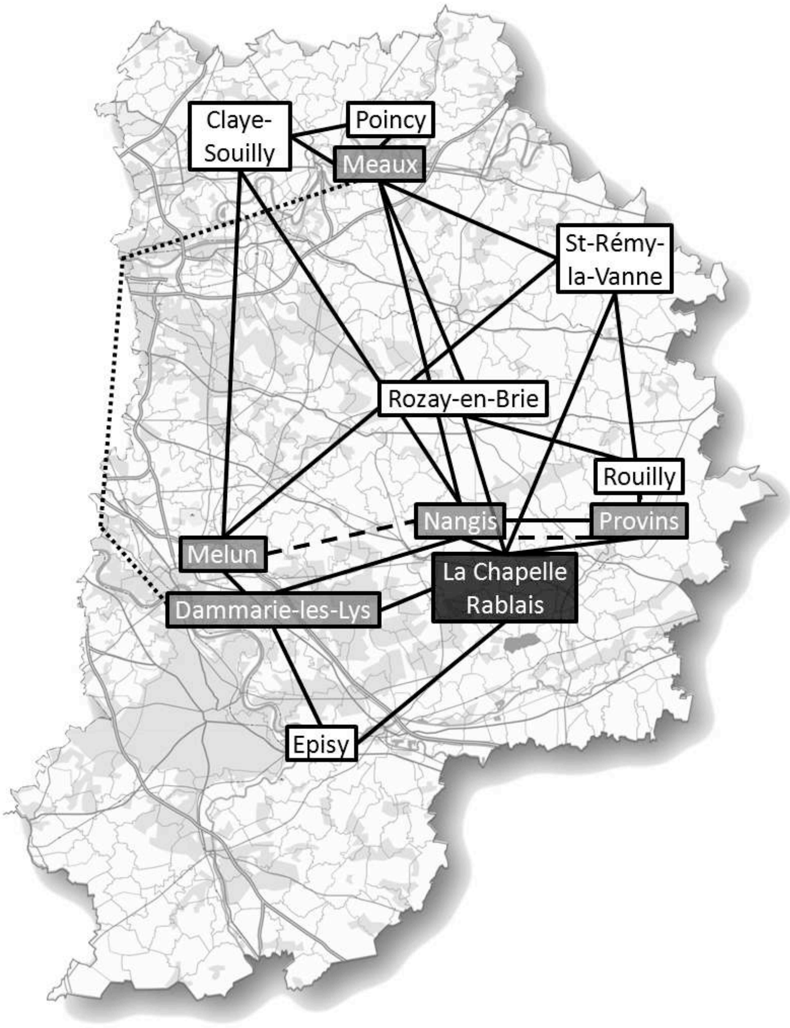
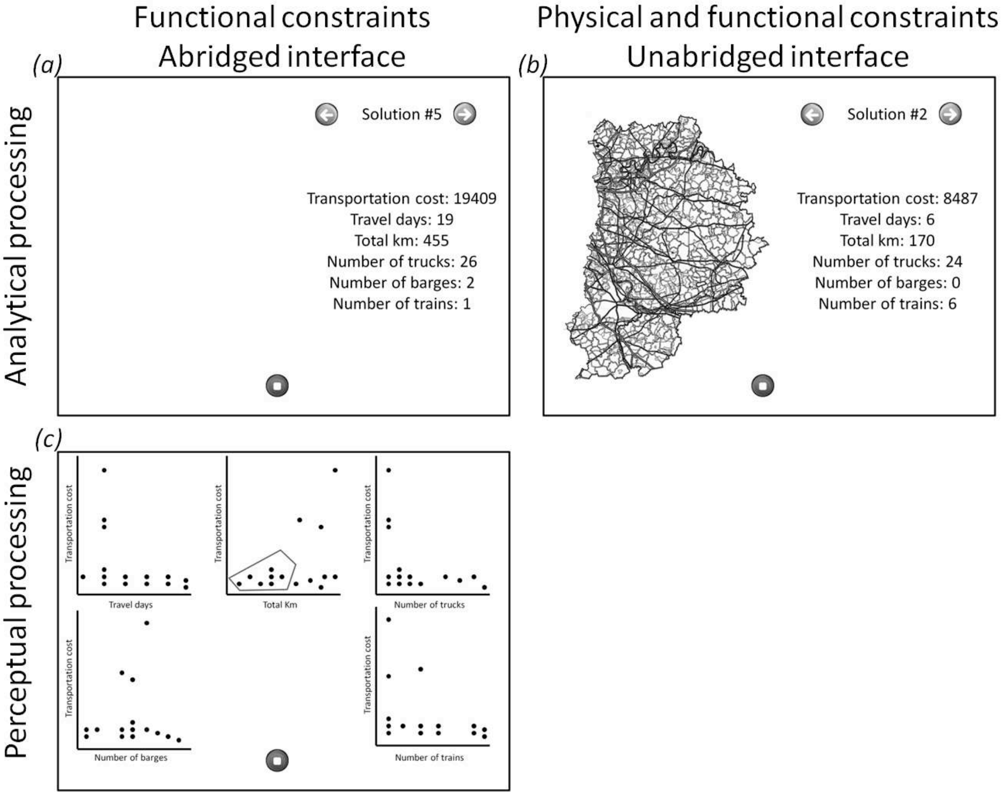


Figure 3. Schematic view of the different locations and distances featured in the experiment. White, gray and black backgrounds indicate the waste collection site and the construction companies, the loading and unloading points for trains and barges, and the producers' depot, respectively. Solid, dotted and dashed lines indicate trucks, barges and train routes, respectively.



Transportation cost: 19409
Travel days: 19
Total km: 455
Number of trucks: 26
Number of barges: 2
Number of trains: 1

Transportation cost: 8487
Travel days: 6
Total km: 170
Number of trucks: 24
Number of barges: 0
Number of trains: 6

Figure 4. Illustrations of the three interfaces used in the experiment. Highlighted routes on the map (b) and axis graduations of (c) are not shown for readability reasons. In Figures (a) and (b), the user browses through the different solutions. In Figure (c) the user sees all the solutions displayed on the interface at the same time.

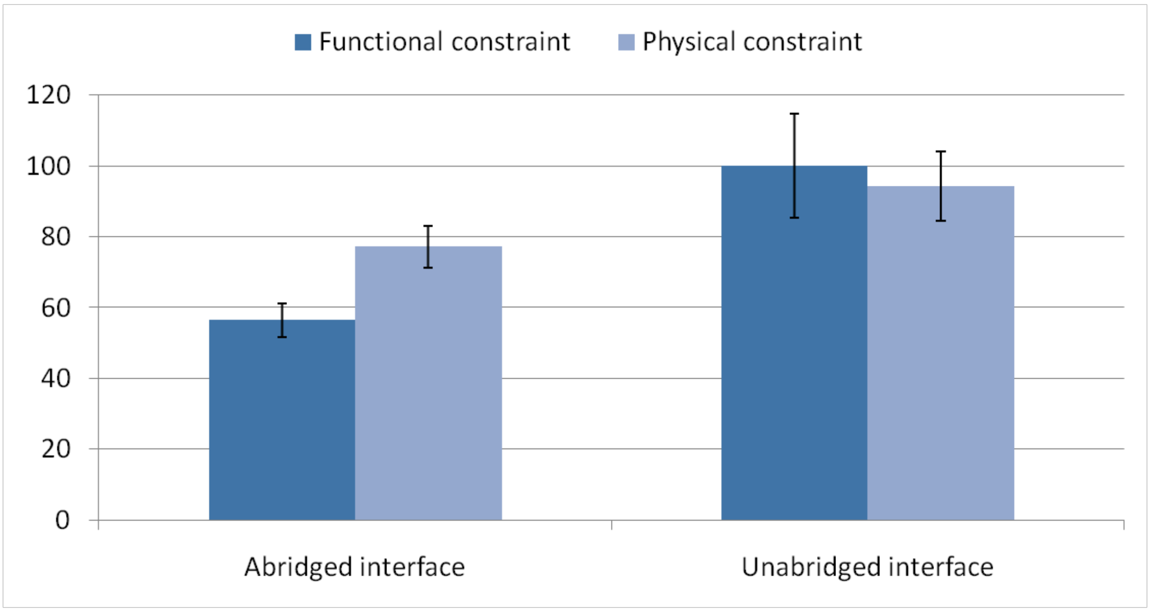


Figure 5. Total time (in seconds) taken to select a solution according to interface type and scenario.

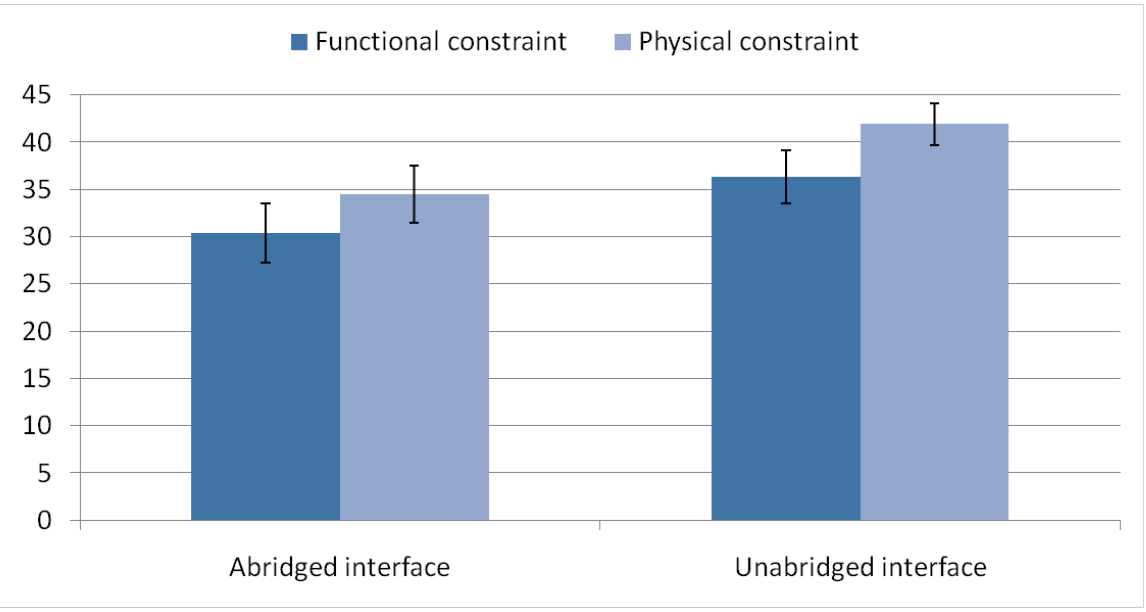


Figure 6. Overall mental workload (NASA-TLX).

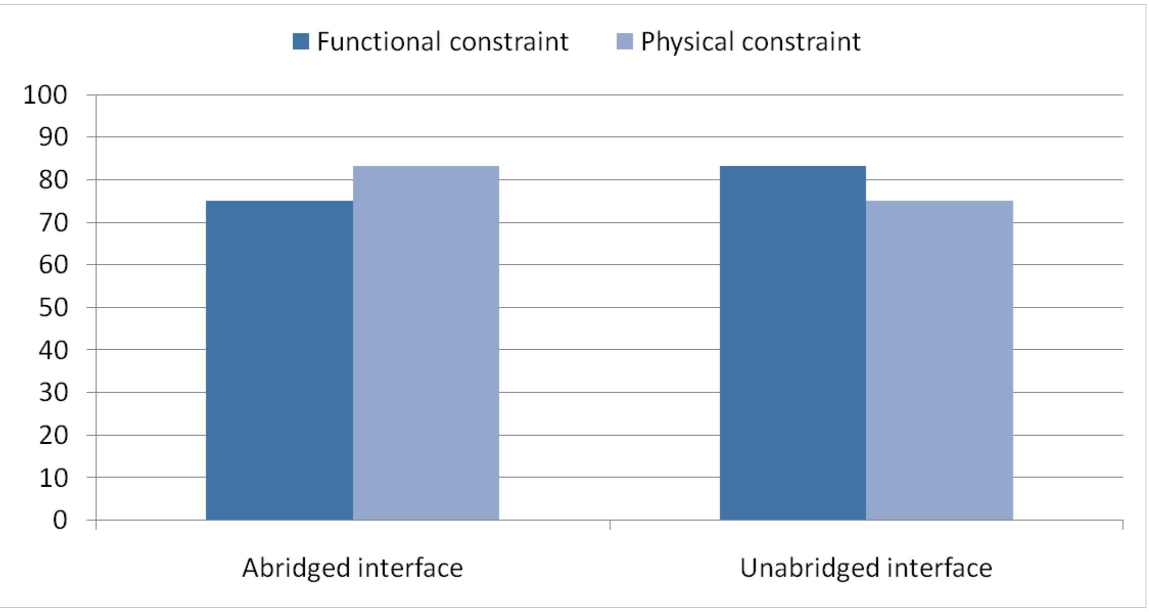


Figure 7. Percentage of participants who successfully solved the problem.

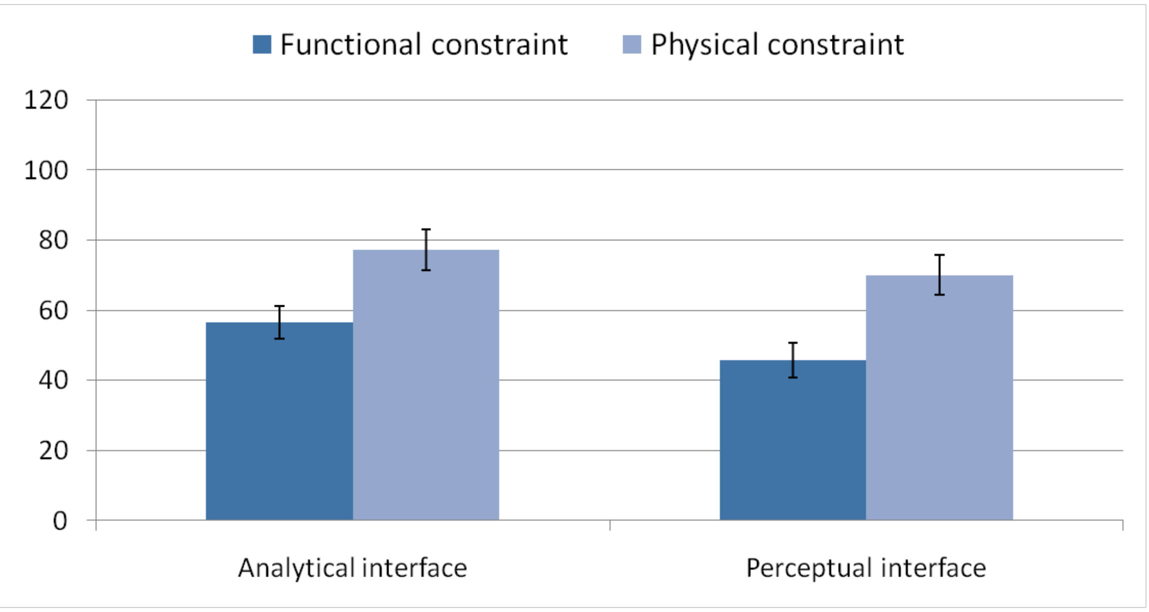


Figure 8. Total time (in seconds) taken to select a solution according to interface type and scenario.

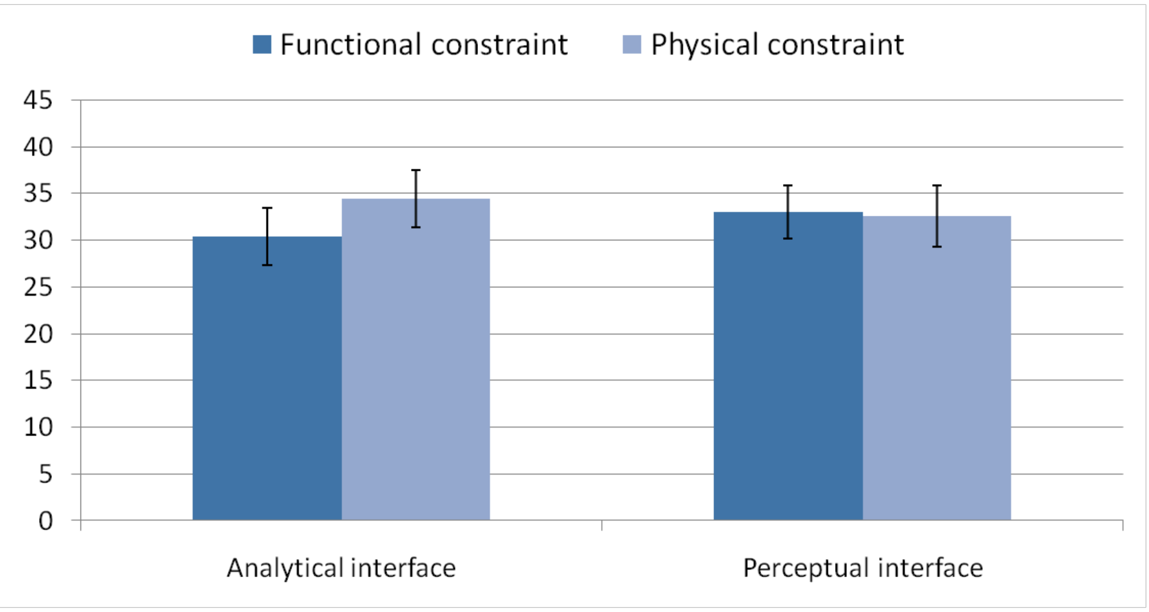


Figure 9. Overall mental workload (NASA-TLX).

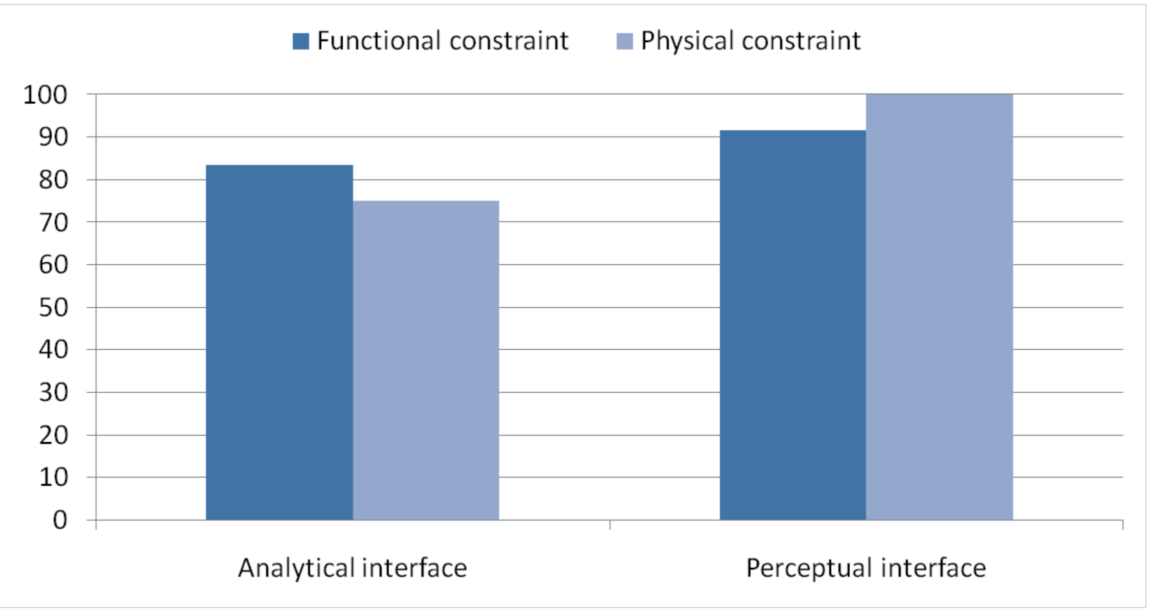


Figure 10. Percentage of participants who successfully solved the problem.

Table 1. Capacity and price constraints for the sites used in the scenarios.

Site	Maximum capacity (tons)	Unloading price (per ton)
Poincy	3,000	0
St-Rémy-la-Vanne	300	+€1.50
Rouilly	500	0
Rozay-en-Brie	1,000	+€1
Episy	50	0
Claye-Souilly (waste collection site)	400,000	-€100

Table 2. Constraints related to each transport mode.

Transport mode	Maximum capacity	Transportation cost for maximum capacity	Average speed
Truck	25 tons	€ 2.50/km	55km/h
Train	500 tons	€ 250/km	18km/h
Barge	400 tons	€ 80/km	8km/h