

RESEARCH ARTICLE

Task-oriented information value measurement based on space-time prisms

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(Received 00 Month 200x; final version received 00 Month 200x)

Recent years have witnessed a large increase in the amount of information available from the Web and many other sources. Such an information deluge presents a challenge for individuals who have to identify useful information items to complete particular tasks in hand. Information value theory (IVT) from economics and artificial intelligence has provided some guidance on this issue. However, existing IVT studies often focus on monetary values, while ignoring the spatiotemporal properties which can play important roles in everyday tasks. In this paper, we propose a theoretical framework for task-oriented information value measurement. This framework integrates information value theory with the space-time prism from time geography and measures the value of information based on its impact on an individual's space-time prisms and its capability of improving task planning. We develop and formalize this framework by extending the utility function from space-time accessibility studies and elaborate it using a simplified example from time geography. We conduct a simulation on a real-world transportation network using the proposed framework. Our research could be applied to improving information display on small-screen mobile devices (e.g., smartwatches) by assigning priorities to different information items.

Keywords: information value; time geography; space-time prism; decision making.

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1. Introduction

Information plays an important role in the daily life of people. Given some critical information, individuals can often complete their tasks in a more effective manner. Accordingly, such critical information has been considered as valuable, and is desired in many decision making scenarios. In recent years, there has been an increasing demand for valuable information, due to several factors. First, a large amount of information is available in today's big data era. Facing this information deluge, individuals often have to search through large amounts of data in order to identify valuable information. This process can become more time-consuming as the volume of data is constantly expanding. Second, mobile devices, such as smartphones, have been widely accepted by the general public. Unlike desktop computers, many mobile devices are equipped with only small screens for information display. The same situation applies to the newly invented wearable devices, such as smartwatches. With the limited display space, it becomes necessary to identify and first show the most valuable information to the end users. Finally, individuals often have to make decisions under time constraints. As a result, it can be helpful for people to learn the information that is most valuable to them within the limited time.

These multiple factors call for a mechanism to quantify the value of information so that it can be prioritized. The value of information, however, does not only depend on the information itself but also the tasks in which the information will be used to support decision making. A piece of information can hardly be considered as useful if it has no influence on completing a targeted task (Frank 2003). Information value theory (IVT) from economics and artificial intelligence has provided some guidance on this topic (Howard 1966). According to IVT, the value of information can be measured as the improvement introduced by the information in completing the task. To quantify this improvement, IVT employs utility functions which assign numeric values to the possible outcomes of the task. Thus, a more desired outcome will be assigned a higher utility value, whereas a less preferred result receives a lower value. A piece of information will then be considered as valuable if it helps to achieve an outcome with a utility value higher than that of the original outcome when this information was not provided. Money, with its root in economics and almost universal exchangeability, has been frequently used in utility functions, and accordingly, the value of information is often quantified as a certain amount of money.

The monetary quantification for information value is useful in applications such as investment analysis and clinical assessment (McFall and Treat 1999, Chen *et al.* 2001). From a spatiotemporal perspective, information can also play the role of informing people about the spatiotemporal changes in the environment. For example, information can update people about the traffic congestion on part of the road network, the unexpected delay of a departure flight, or the location change of an event. Such a role is important, because without the corresponding information, people could be late for an appointment due to the traffic jam, arrive too early at the airport finding the departure time has been postponed, or even reach at the wrong location for the event. However, this spatiotemporal role has been rarely considered in existing information value research.

This paper fills this gap by proposing a framework that measures the value of information from a spatiotemporal perspective. Specifically, we look into the tasks that an individual needs to complete and examine how information can help inform the individual about the spatiotemporal changes of tasks. The space-time prism from time geography has provided an approach for modeling the spatiotemporal properties of tasks (Hägerstrand 1970), and therefore has been employed in our proposed framework. **The**

contributions of this work are twofold:

- From a theoretical point of view, this paper proposes a framework which integrates information value theory with space-time prisms in time geography. On one hand, this framework provides an approach for measuring the value of information from a spatiotemporal perspective. On the other hand, such a framework also demonstrates a novel application of the space-time prism which is a classic method in GIScience.
- From a practical point of view, the proposed framework contributes to solving problems that require an understanding of information priorities. Example applications include selective information display on small-screen devices as well as personalized information push in location-based services.

For conciseness, we use the phrase *information item* instead of *a piece of information* to represent a single unit of information. Particularly, we focus on the information which can be typically received or retrieved by today's mobile devices and which is related to spatiotemporal properties. Examples of an *information item* can be “the temperature at the current location is 75 °F”, “there is a traffic jam on Highway 101 between exit 98 and exit 99, which causes about 10-minute delay”, “the arrival time of flight UA 723 has been delayed from 8:00 pm to 8:30 pm”, and so forth. While we have represented these information items as natural language descriptions for readability, information is typically represented in formats that can be directly processed by machines.

The remainder of this paper is organized as follows. Section 2 provides a review of the related work on measuring information value, as well as the theories and methods used in the proposed framework. Section 3 gives a formal problem definition for the task-oriented information value measurement. Based on this definition, section 4 presents the theoretical framework by developing an extended utility function and a general workflow for assigning priorities to multiple information items. In section 5, we illustrate the use of the proposed framework based on a simplified example from time geography. Section 6 simulates a scenario using a transportation network from the city of Santa Barbara, California, USA. Finally, section 7 concludes this work and discusses future directions.

2. Related work

In this section, we review existing research in measuring the value of information. In addition, we also provide brief descriptions on the theories and methods which serve as the foundations of our framework.

2.1. Measuring information value

Information has intrigued researchers for decades. Back in 1949, Shannon and Weaver published a book on *information theory* which measures information based on the probability of occurrence of each code and employs the unit *bit* to quantify the amount of information. While such an approach has been widely adopted nowadays to describe the size of data, it does not consider the semantics of information. Howard (1966) proposed *information value theory* which connects information with decision making and examines the influence of information on the outcomes of a decision. As a general framework, IVT has been applied to many domains, such as policy analysis (Stokey and Zeckhauser 1978), clinical trials (Willan and Pinto 2005), and artificial intelligence (Russell and Norvig 2010).

Measuring the value of information, especially geographic information, has also attracted attentions from GIScience community. In 1993, the National Center for Geo-

graphic Information and Analysis (NCGIA) proposed a research initiative on the use and value of geographic information (Onsrud and Calkins 1993), although no definite conclusion was reached then. Goodchild (2003) asked the question: if geographic information is to be traded as a commodity, how could we quantify its value? To answer this question, he proposed to decompose geographic information into atomic tuples, called *geo-atoms*, which can be in the form of $\langle \mathbf{x}, z \rangle$ with \mathbf{x} representing a point in space-time and z denoting the associated attribute. He then proposed to measure the number of geo-atoms as a quantification for the value of geographic information. While this atom view has been adopted in geographic information representation (Goodchild *et al.* 2007, Liu *et al.* 2008, Pultar *et al.* 2010, Wang *et al.* 2015), it does not take into account the decisions that information will be used for. Frank (2003) proposed the concept of *pragmatic information content* which was defined as the minimal amount of data necessary for the user to make the decision. He contended that the usefulness of information should be determined with respect to a decision context, and employed a route description example to demonstrate his framework. In the domain of location-based services (LBS), while the value of information has not been explicitly discussed, there exists a general demand for identifying important information based on the tasks of users. For example, Raubal *et al.* (2004) presented a conceptual framework which integrates time geography with an extended theory of affordance, and such a framework is designed to provide location-based information that can better fit the tasks and preferences of individuals. Zipf and Jöst (2006) discussed the implementation of adaptive geographic information services which aim at generating maps based on the user's task needs.

Our work can be distinguished from the previous studies in several aspects. Compared with the existing IVT research, the proposed framework presents a spatiotemporal approach for measuring information value, which innovatively integrates the space-time prism with IVT. Additionally, this work focuses on the information that can be received or retrieved by mobile devices, and therefore is not constrained by the two typical assumptions in traditional IVT research: 1) information is costly; 2) the content of information cannot be known beforehand. A lot of information nowadays can be retrieved from Web services for free (although time and data transmission cost may still apply), and the content of information can be previewed by software applications. Compared with the information value research in GIScience community, our work is in the same direction with related studies, in which we connect the value of information to decision making and attempt to identify the information that fits into the tasks of individuals. Our proposed framework employs utility functions to quantify the improvement introduced by information, thereby presenting a more quantitative approach for information value measurement. Our framework can also assign priorities to multiple information items.

2.2. Foundations of the proposed framework

Information value theory. While IVT has been mathematically formalized in multiple ways in different studies (Szaniawski 1967, Schlee 1991, Russell and Norvig 2010), its core idea is to calculate the utility difference before and after an information item has been introduced into decision making. Such an idea can be represented as equation (1)

$$V(I) = U(d_{new}) - U(d_{original}) \quad (1)$$

where I denotes the information item, $d_{original}$ represents the original decision without information I , $U(d_{original})$ represents its utility, $U(d_{new})$ represents the utility of the new decision d_{new} after information I has been introduced, and $V(I)$ represents the value of I . In existing studies, information has often been assumed as *perfect*, i.e., information can accurately reflect the ground truth (Felli and Hazen 1998, Brennan *et al.* 2007). Such an assumption rarely holds in reality due to factors such as the measurement uncertainty. In this research, however, we still make the perfect information assumption, since this is a first step to establish the overall framework.

Space-time prism. The space-time prism is a fundamental concept in time geography. It models the spatiotemporal constraints under which an individual's activities can take place (Hägerstrand 1970). A space-time prism can be represented in a 2D (or 3D) coordinate system, with x (and y) axes representing space, and the vertical axis t representing time. The tasks of an individual can be classified into four groups according to their spatiotemporal properties (Kim and Kwan 2003, Chen and Kwan 2012): (1) fixed location and fixed time; (2) fixed location and flexible time; (3) flexible location and fixed time; (4) flexible location and flexible time. The prism depicts the space-time budget that the individual has; tasks outside the prism cannot be completed within the budget.

Utility-based accessibility measurement. Accessibility measures the freedom of an individual to participate in activities in the environment (Weibull 1980). Spatiotemporal properties have been frequently examined in existing accessibility research (Lenntorp and Hort 1976, Burns 1979, Miller 1999, Kwan 1999, Hsu and Hsieh 2004). To measure the value of information from a spatiotemporal perspective, our framework employs and extends the utility functions which were traditionally used for accessibility measurement. Specifically, we build our utility function based on the research from Burns (1979), Miller (1999), and Ettema and Timmermans (2007). Burns (1979) proposed a general function for measuring accessibility utility, and such a function was realized into a computational procedure on transportation networks by Miller (1999). Equation (2) shows this function

$$U(a, D, T) = a^\alpha D^\beta \exp(-\lambda T) \quad (2)$$

where a denotes the attractiveness of the location, D represents the stay duration an individual can have at the location, and T is the required travel time. α , β and λ are all positive parameters which respectively determine the influences of the three factors on the utility value. This function measures the utility of accessibility by considering not only whether an individual can reach a location, but also the attractiveness of the location as well as the individual's stay duration. Ettema and Timmermans (2007) extended this utility function by introducing penalties for early and late arrivals. The extended utility function is depicted in equation (3)

$$U(a, D, T, SDE, SDL) = a^\alpha D^\beta \exp(-\lambda T) \exp(-\gamma_1 SDE) \exp(-\gamma_2 SDL) \quad (3)$$

where SDE represents *Schedule Delay Early*, and SDL represents *Schedule Delay Late*. γ_1 and γ_2 are positive parameters which determine the penalties for the two factors respectively. This extension recognizes that arriving too early or too late at a location for a task (e.g., attending a meeting) can have negative impact on the utility value. As shown in equation (3), the utility U will monotonically increase with the stay duration D . However, from a perspective of completing tasks, it is often unnecessary to stay at

a location longer when the task has already been finished. Our work further extends equation (3) to measure information value based on tasks.

3. Problem definition

This section provides a formal definition for the problem of task-oriented information value measurement. Let a set \mathcal{G} , with elements g_1, g_2, \dots, g_m , represent the *tasks* that an individual needs to complete¹. A task plan is represented as *plan*, while *plan*^{*} denotes the *optimal plan* that maximizes the utility of completing all tasks in \mathcal{G} . To find *plan*^{*}, it is necessary to formalize the properties of tasks.

Many tasks in our everyday life have a variety of properties that need to be considered (Abdalla and Frank 2012). To complete one specific task, an individual may need to be present at a particular location and time and may have to fulfill certain pre-conditions (e.g., carrying a laptop if the task is to make a presentation). In this work, we focus on a task's spatiotemporal properties although the pre-conditions are important as well.

We first discuss the spatial properties of a task. Let g_j be a particular task in \mathcal{G} , a set \mathcal{L}_j of n_j elements, namely $l_{j1}, l_{j2}, \dots, l_{jn_j}$, is used to denote the possible locations where g_j can be completed. For example, if g_j is to take a friend for lunch, then \mathcal{L}_j may contain *restaurant A*, *restaurant B*, and *restaurant C*. This formalization recognizes that one task can be supported by multiple locations, and the individual may need to make a choice. When a task requires one fixed location (e.g., attending a meeting), then the set \mathcal{L}_j will contain only one element. For tasks that require multiple fixed locations (e.g., a postman may have to travel to a number of locations to finish the task of delivering mails), we can decompose one complex task into several subtasks based on each of these locations. We borrow the concept of *attractiveness* from Burns (1979) and Miller (1999) (see equation (2)), and use a set \mathcal{A}_j of n_j elements, $a_{j1}, a_{j2}, \dots, a_{jn_j}$, to represent the attractiveness of the locations. In the context of task planning, each a_{jk} should be interpreted as the capability of location l_{jk} to help the individual complete task g_j .

There are several temporal properties related to tasks. The first one is the preferred arrival time (PAT), and we use PAT_{jk} to denote the PAT for task g_j at l_{jk} . Time flexible tasks may not have a pre-defined PAT. In such cases, the PAT can be considered as the same as the individual's actual arrival time (AAT). Another temporal property is the duration that an individual needs to stay at a location to complete the task. Such a stay duration can vary at different locations for even the same task. Consider the task of taking a friend for lunch again. A fast-food place often takes shorter time to prepare food than a traditional restaurant does. This stay duration information could be estimated by the service providers and be made available online. We use a set \mathcal{D}_j of n_j elements, $D_{j1}, D_{j2}, \dots, D_{jn_j}$, to represent the stay durations at these locations. A third temporal property is the waiting time which can also impact the utility of a task plan. However, a waiting time problem can be transformed into an early arrival case, since arriving early also means the individual has to wait until the task begins.

With the spatiotemporal properties formalized, a task plan can be constructed by selecting one location l_{jk} for each task g_j in \mathcal{G} . We can then calculate the utility for each task plan using a utility function U , and find the optimal *plan*^{*} using equation (4)

$$plan^* = \arg \max_{plan} U(plan) \quad (4)$$

¹Instead of using t to represent *task*, we use g to denote the meaning of *goal*; t has been reserved for *time*.

where $plan^*$ represents the optimal plan under the current situation. When certain spatiotemporal properties change, an information item can perform the role of updating the individual on these changes. However, before such information is provided, a lag can exist in the individual's understanding, i.e., the individual is unaware of these changes. With this lag, the individual would still execute the originally optimal plan, although such a plan is no longer optimal given the current situation. We use $U(plan^*)$ to represent the utility that the individual thinks the optimal plan could achieve, and use $U'(plan^*)$ to denote the utility that the plan can actually achieve. After the information is provided, the individual can accordingly update his/her understanding, and develop a new optimal plan $plan_{new}^*$. The actual utility of the new optimal plan is represented as $U'(plan_{new}^*)$.

Now, given a set of information items \mathcal{I} , how can we determine their relative values with regard to the tasks in \mathcal{G} ? We formalize this problem as below:

TASK-ORIENTED INFORMATION VALUE MEASUREMENT: *given a set of tasks \mathcal{G} , their formalized spatiotemporal properties, and a set of information items \mathcal{I} , measure the relative values of the elements in \mathcal{I} based on the utility improvements they can introduce to the tasks in \mathcal{G} .*

4. Theoretical framework

Based on the formalized problem, this section presents a theoretical framework for task-oriented information value measurement. Such a framework extends the utility function in space-time accessibility studies and employs the utility improvement to quantify information value. We also present a general workflow to assign priorities to multiple information items.

4.1. Extended utility function

A task plan is designed to complete the tasks of an individual. Accordingly, the overall utility of a task plan depends on the utilities derived from each of the tasks when such a plan is executed. Thus, we first develop a utility function for a single task.

Let a vector \mathbf{S}_{jk} represent the spatiotemporal properties of using location l_{jk} to complete task g_j

$$\mathbf{S}_{jk} = \langle l_{jk}, a_{jk}, PAT_{jk}, AAT_{jk}, D_{jk}, D'_{jk} \rangle \quad (5)$$

where l_{jk} denotes the location, a_{jk} represents the attractiveness of the location, PAT_{jk} is the preferred arrival time for task g_j at l_{jk} , AAT_{jk} is the actual arrival time at the location, D_{jk} is the preferred stay duration to complete the task, and D'_{jk} is the actual stay duration that the individual can have. Based on \mathbf{S}_{jk} , a utility function can be developed by extending the ones from the literature (Burns 1979, Miller 1999, Ettema and Timmermans 2007). Equation (6) shows this extended function

$$U(\mathbf{S}_{jk}) = a_{jk}^\alpha f(D_{jk}, D'_{jk})h(PAT_{jk}, AAT_{jk}) \quad (6)$$

In this utility function, a_{jk} denotes the capability of location l_{jk} in supporting task g_j . We define a_{jk} as a real number in $[0, 1]$, with 1 for a location that satisfies all requirements of g_j , and 0 for a location that does not meet any requirement. When a task has to be executed at a fixed location, 1 can be assigned to this unique location. α is a positive parameter which determines the penalty for a location that does not satisfy

some requirements (i.e., $a_{jk} < 1$). A larger α will put more penalty on these locations.

$f(D_{jk}, D'_{jk})$ is a benefit function which measures the utility of the individual's stay duration at location l_{jk} . This function is formalized as below

$$f(D_{jk}, D'_{jk}) = \left[\min \left\{ \frac{D'_{jk}}{D_{jk}}, 1 \right\} \right]^\beta \quad (7)$$

where D_{jk} is the preferred stay duration at location l_{jk} to complete task g_j , and D'_{jk} is the actual stay duration that the individual can have. When the task cannot be fully completed within D'_{jk} (i.e., $D'_{jk} < D_{jk}$), the utility of choosing location l_{jk} for task g_j will decrease, and the decreasing severity depends on parameter β . The value range of the utility function is $[0, 1]$, with $f = 1$ indicating that the individual has enough time to complete the task, and $f < 1$ indicating that the individual can only partially or even not (i.e., $f = 0$) finish the task. For tasks which have a hard requirement on stay duration (e.g., a formal meeting), we can set β as $+\infty$ and thus $f = 0$ when $D'_{jk} < D_{jk}$. It is worth noting that equation (7) is one possible realization of the stay-duration utility function. It assumes that staying at a place longer than the preferred time will neither increase or decrease the utility. This utility function could be modified to capture other effects, e.g., the utility may decrease when the individual stays at a place longer.

$h(PAT_{jk}, AAT_{jk})$ measures the utility with regard to the preferred arrival time and the actual arrival time. It is defined as below

$$h(PAT_{jk}, AAT_{jk}) = \exp(-\gamma_1(PAT_{jk} - AAT_{jk})^+) \exp(-\gamma_2(AAT_{jk} - PAT_{jk})^+) \quad (8)$$

where $(PAT_{jk} - AAT_{jk})^+ = \max\{(PAT_{jk} - AAT_{jk}), 0\}$ representing the early arrival, and $(AAT_{jk} - PAT_{jk})^+ = \max\{(AAT_{jk} - PAT_{jk}), 0\}$ representing the late arrival. Both γ_1 and γ_2 are positive parameters that determine the respective penalties, and the value of $h(PAT_{jk}, AAT_{jk})$ is within $(0, 1]$. Two special cases need to be discussed. First, when task g_j is a flexible task, we let $PAT_{jk} = AAT_{jk}$, and therefore there is no early or late arrival penalty, i.e., $h(PAT_{jk}, AAT_{jk}) = 1$. Second, when waiting time is involved, we let $PAT_{jk} = AAT_{jk} + T_w$ where T_w is the waiting time. Such a formalization allows waiting time to be handled as early arrival. In addition, for tasks with fixed PAT_{jk} and fixed D_{jk} , the actual arrival time AAT_{jk} can determine the actual stay duration D'_{jk} using: $D'_{jk} = \max\{(D_{jk} - (AAT_{jk} - PAT_{jk})^+), 0\}$.

Since all factors in the extended utility function have values between 0 and 1, the utility value of completing task g_j at location l_{jk} is also in $[0, 1]$. This implies that a location which satisfies all spatiotemporal requirements of a task can achieve a full score of 1, whereas 0 will be assigned to a location where the individual cannot complete the task. The parameters, α , β , γ_1 , and γ_2 , provide flexibility for controlling the penalties when certain requirements cannot be fulfilled. These parameters reflect the appreciation towards corresponding factors, and can be estimated by conducting human participant experiments. For example, participants could be asked to evaluate the consequences of early arrival and late arrival, and Likert scales could be used to quantify their opinions.

4.2. Utility of a task plan

Given the vector representation of a single task (equation (5)), a task plan can be represented as a sequence of spatiotemporal vectors

$$plan = \{\mathbf{S}_{1k_1}, \mathbf{S}_{2k_2}, \dots, \mathbf{S}_{mk_m}\} \quad (9)$$

where \mathbf{S}_{jk_j} is the spatiotemporal vector of completing task g_j at location l_{jk_j} . It is worth noting that we are using \mathbf{S}_{jk_j} , instead of \mathbf{S}_{jk} , to represent the spatiotemporal vector of task g_j , since multiple tasks are being considered in a plan.

We consider a plan as *valid* if it achieves positive utilities for all tasks in \mathcal{G} ; (10) represents the set of valid plans

$$\{plan \mid \forall \mathbf{S}_{jk_j} \in plan, U(\mathbf{S}_{jk_j}) > 0\} \quad (10)$$

We consider a plan as *invalid*, if it provides zero utility for at least one of the tasks in \mathcal{G} , and these invalid plans are represented using a set as (11). The utility of an *invalid plan* is defined as 0.

$$\{plan \mid \exists \mathbf{S}_{jk_j} \in plan, U(\mathbf{S}_{jk_j}) = 0\} \quad (11)$$

Accordingly, the overall utility of a task plan can be calculated by summing up the utilities of single tasks and including the travel time between tasks

$$U(plan) = \exp(-\lambda \sum_{j=1}^m T_{j-1,j}) \sum_{j=1}^m U(\mathbf{S}_{jk_j}) \quad (12)$$

where $T_{j-1,j}$ denotes the travel time from task g_{j-1} to g_j , and λ is a positive parameter that determines the penalty of travel time.

4.3. A general workflow

Based on the utility function for task plans, we develop a general workflow for measuring the relative values of multiple information items and assigning priorities to them. Figure 1 illustrates this workflow.

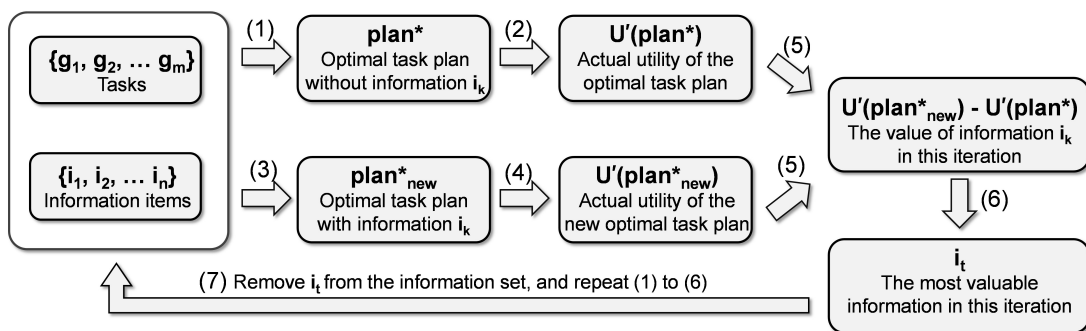


Figure 1. A general workflow for assigning priorities to multiple information items.

In this workflow, step (1) to (4) calculate the utilities of the optimal task plans before and after the information item i_k has been provided. Step (5) calculates the relative

value of i_k based on the utility difference. Then, step (6) applies step (1) to (5) to each information item in the set, and identifies the most valuable information i_t in this iteration. Step (7) removes i_t from the information set, and starts a new iteration by repeating step (1) to (6) to identify the next most important information. It is worth noting that while the workflow will assign numeric values to information items during each iteration, these numbers are relative and cannot be compared across iterations. The most important output from this workflow is a ranking which can be used to determine the priorities of different information items.

5. Measuring information value based on tasks

This section employs a simplified time geography example to illustrate the proposed framework. Specifically, we use the framework to measure three types of information which are related to travel velocity, location, and temporal properties.

5.1. A simplified example in time geography

In this example, an individual starts from location l_0 at time t_0 . She has two tasks g_1 and g_2 to complete. g_1 is a flexible task which does not require a PAT, and can be completed at either l_{11} or l_{12} . g_2 is a task that has a fixed PAT t_2 and a fixed location l_{21} . Figure 2 shows the time, locations, and a space-time prism of this example. For clarity of illustration, the space is represented as one dimension.

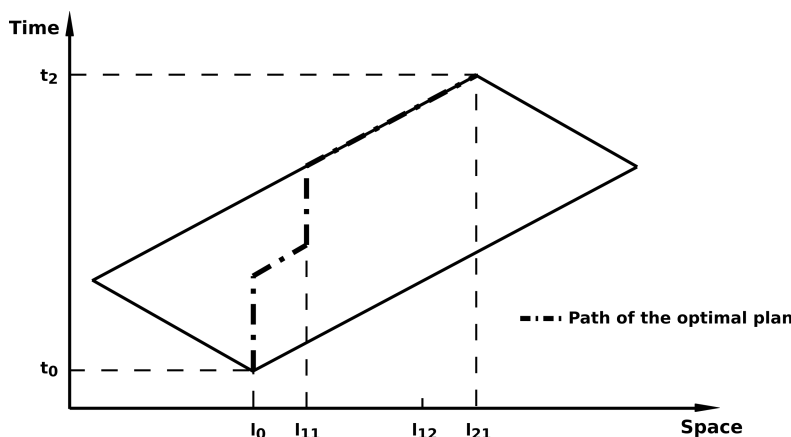


Figure 2. A space-time prism and a potential optimal plan for tasks g_1 and g_2 .

For task g_1 , the penalties of early arrival and late arrival do not apply, since it is a flexible task and does not involve waiting time currently. Therefore, $h(PAT_{1k_1}, AAT_{1k_1}) = 1$, and the utility of completing task g_1 becomes

$$U(\mathcal{S}_{1k_1}) = a_{1k_1}^\alpha f(D_{1k_1}, D'_{1k_1}) \quad k_1 \in \{1, 2\} \quad (13)$$

To enhance the example setting, we add the following conditions: 1) $a_{11} > a_{12}$, i.e., location l_{11} provides better support for g_1 than location l_{12} ; 2) $D_{11} = D_{12}$, i.e., location l_{11} requires the same amount of stay duration as location l_{12} does; 3) $D_{1k_1} = D'_{1k_1}$, $k_1 \in \{1, 2\}$, i.e., the current spatiotemporal constraints allow the individual to stay enough time at either l_{11} or l_{12} to complete g_1 .

For task g_2 , it has a fixed PAT t_2 , and therefore schedule delay should be considered. Since l_{21} is the fixed location for task g_2 , its capability to support the task a_{21} is defined

as 1. Besides, as there is no additional temporal constraint for g_2 , the individual can stay at l_{21} for enough time. Thus, $f(D_{21}, D'_{21}) = 1$. Therefore, the utility of completing task g_2 at l_{21} becomes

$$U(S_{2k_2}) = h(PAT_{2k_2}, AAT_{2k_2}) \quad k_2 \in \{1\} \quad (14)$$

The overall travel time will be the same regardless of whether l_{11} or l_{12} is chosen for task g_1 , since both are on the way to l_{21} in this one dimensional space. Figure 2 shows the spatiotemporal path of an optimal plan $plan^*$: the individual stays at l_0 for a while to avoid the penalty of early arrival at l_{21} ; she then travels to l_{11} to complete task g_1 since this location provides better support for g_1 ; after that, the individual travels to l_{21} and arrives on time for task g_2 .

Based on this example, we use the proposed framework to measure the values of different types of information. The information items, which will be discussed in the following subsections, are received before travel, so that the individual can change her task plan accordingly to fit the current situation.

5.2. Measuring the value of traffic information

Consider the situation in which an accident has happened near l_{11} and has caused traffic congestion in that area (Figure 3). An information item $I_{traffic}$ can tell the individual the current travel velocity given this congestion. What would be a proper value for $I_{traffic}$?

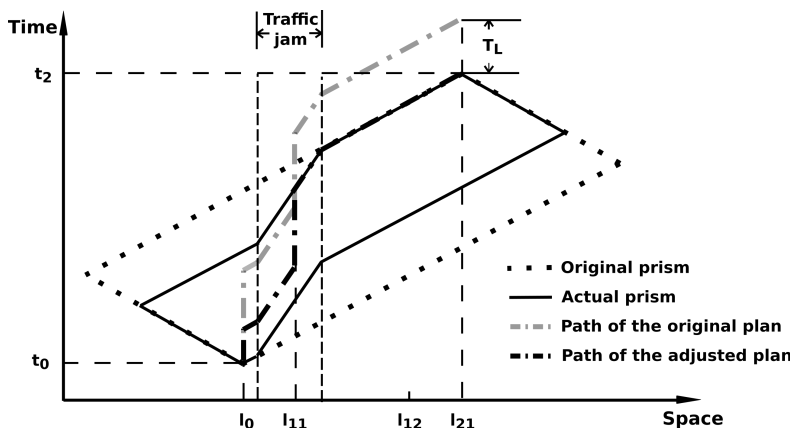


Figure 3. The changed space-time prism, the actual path of the original plan, and the path of the adjusted plan.

Following the proposed framework, we can first calculate the utility of the original task plan without $I_{traffic}$. Without more information, the individual will execute the original $plan^*$. Due to the traffic congestion, the individual will not be able to travel at the original speed, and consequently, will arrive at l_{21} late. The gray line in Figure 3 shows the actual spatiotemporal path of executing $plan^*$. We assume that the individual will exactly follow the original plan, although in reality the individual might flexibly change her plan by, e.g., staying at l_{11} for less time to mitigate the consequence of late arrival at l_{21} . Since there could be innumerable ways of making plan changes, this assumption provides one approach to estimate the actual utility of $plan^*$. Let $T'_{j-1,j}$ be the actual travel time given the congestion, the actual utility of $plan^*$ can be calculated using equation (15),

where T_L denotes the late arrival time.

$$U'(plan^*) = \exp(-\lambda \sum_{j=1}^2 T'_{j-1,j}) [a_{11}^\alpha + \exp(-\gamma_2 T_L)] \quad (15)$$

With $I_{traffic}$, the individual can adjust her plan accordingly. She can choose location l_{12} for g_1 or can still choose l_{11} but start from l_0 earlier. No matter whether l_{11} or l_{12} is chosen, the individual will have to endure the traffic jam. Since l_{11} provides a higher capability to support g_1 , the individual can choose to start earlier from l_0 , then go to l_{11} for task g_1 , and finally arrive at l_{21} on time (see the adjusted plan in Figure 3). The utility of $plan_{new}^*$ is

$$U'(plan_{new}^*) = \exp(-\lambda \sum_{j=1}^2 T'_{j-1,j}) (a_{11}^\alpha + 1) \quad (16)$$

Thus, the value of $I_{traffic}$ can be measured by its capability in helping avoid late arrival

$$V(I_{traffic}) = U'(plan_{new}^*) - U'(plan^*) = \exp(-\lambda \sum_{j=1}^2 T'_{j-1,j}) [1 - \exp(-\gamma_2 T_L)] \quad (17)$$

5.3. Measuring the value of location information

Assume the location of task g_2 has been changed from l_{21} to l'_{21} , and an information item I_{loc} can inform the individual about this change. This situation happens occasionally when an event (e.g., a meeting) changes its location, and a notification may be sent out. What would be a suitable value for I_{loc} ? Figure 4 shows the new location l'_{21} , and the changed space-time prism.

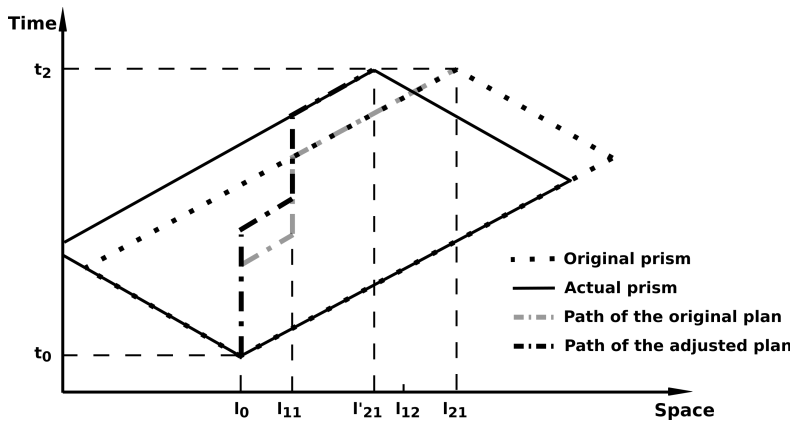


Figure 4. Location change for task g_2 , and the path of the adjusted plan.

To estimate the value of I_{loc} , we start by calculating the utility of the original task plan $plan^*$. Without the location change information, the individual should have no difficulty in completing task g_1 , but will arrive at the wrong location for g_2 . Consequently, zero utility will be derived for task g_2 , and $plan^*$ will become *invalid*. Thus, $U'(plan^*) = 0$.

With I_{loc} , the individual can adjust the original plan by staying at l_0 even longer, then

traveling to l_{11} to complete g_1 , and finally arriving at l'_{21} on time. The overall travel time is also shortened since l'_{21} is closer to l_0 . Let $T'_{j-1,j}$ denote the new travel time, and the utility of $plan_{new}^*$ is

$$U'(plan_{new}^*) = \exp(-\lambda \sum_{j=1}^2 T'_{j-1,j})(a_{11}^\alpha + 1) \quad (18)$$

As a result, the value of the location change information can be calculated as: $V(I_{loc}) = U'(plan_{new}^*) - U'(plan^*) = U'(plan_{new}^*)$.

5.4. Measuring the value of temporal information

This subsection discusses two types of temporal information: preferred arrival time and waiting time.

5.4.1. Information about the preferred arrival time

Consider the situation in which the PAT for g_2 has been postponed from t_2 to t'_2 . Such a situation is not unusual. For example, let g_2 be the task of picking up a guest from the airport, and t_2 can be the arrival time of the flight. The flight can get delayed, and the airline may provide an updated arrival information I_{PAT} . How much value would I_{PAT} be worth? Figure 5(a) illustrates the change of the PAT.

Without I_{PAT} , the individual will execute the original plan $plan^*$, which will have no issue in completing g_1 . However, the individual will arrive at l_{21} earlier than the actual PAT t'_2 . Thus, the penalty of early arrival will apply. The utility of $plan^*$ is

$$U'(plan^*) = \exp(-\lambda \sum_{j=1}^2 T_{j-1,j})[a_{11}^\alpha + \exp(-\gamma_1(t'_2 - t_2))] \quad (19)$$

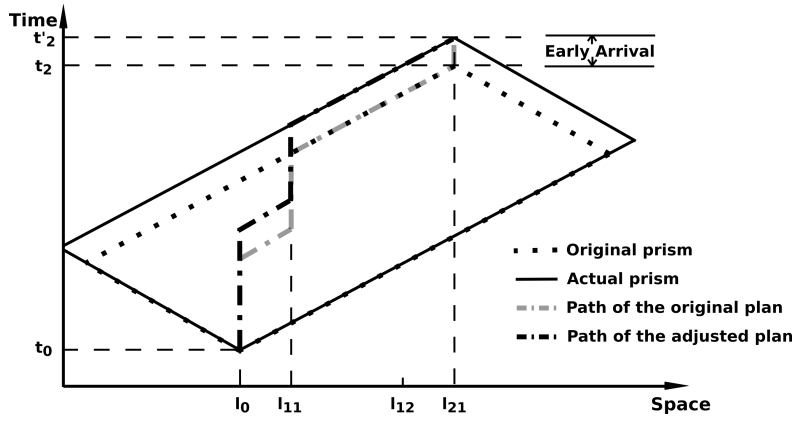
With I_{PAT} , the individual can adjust the original plan by starting from l_0 later to avoid early arrival. The utility of $plan_{new}^*$ can be calculated using equation (20), and the value of I_{PAT} is the utility difference between equation (19) and (20).

$$U'(plan_{new}^*) = \exp(-\lambda \sum_{j=1}^2 T_{j-1,j})(a_{11}^\alpha + 1) \quad (20)$$

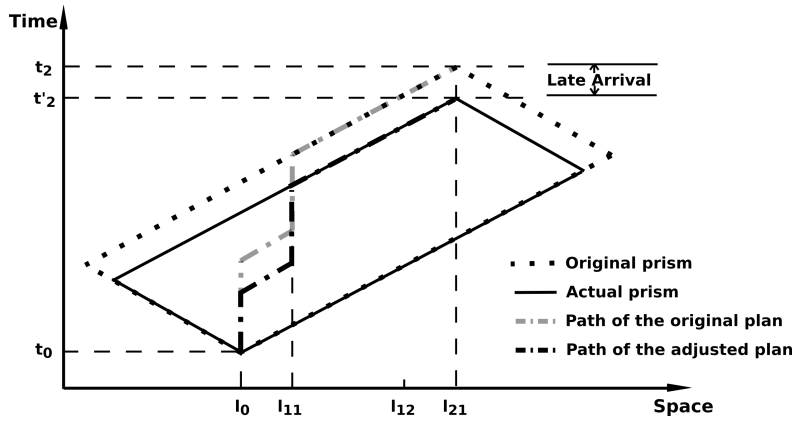
The PAT of a task could also be brought ahead in some other cases. For example, the flight could arrive earlier than the scheduled time. Figure 5(b) shows such a case. Without additional information, the individual will still execute $plan^*$ and will arrive at l_{21} late. While this late is generally considered as fine from a social perspective, we nevertheless let our guest wait in the airport. As a result, the penalty of late arrival could be applied, and the utility of $plan^*$ will become

$$U'(plan^*) = \exp(-\lambda \sum_{j=1}^2 T_{j-1,j})[a_{11}^\alpha + \exp(-\gamma_2(t_2 - t'_2))] \quad (21)$$

With I_{PAT} , the individual can start earlier to avoid the late arrival (see Figure 5(b)). The value of I_{PAT} can be calculated in a similar way like the early arrival case.



(a)



(b)

Figure 5. The adjusted plans based on the PAT changes of task g_2 : (a) $t'_2 > t_2$; (b) $t'_2 < t_2$.

5.4.2. Information about the waiting time

Consider the situation in which a queue of people are waiting at location l_{11} for its service and an information item I_{wait} can tell the individual about the approximate waiting time. How can we assign a proper value to I_{wait} ?

Without I_{wait} , the individual will execute $plan^*$ and may have to wait at l_{11} for T_w before she can start g_1 . The gray line in Figure 6(a) shows the actual spatiotemporal path of $plan^*$. As a result, the penalties of waiting time at l_{11} and late arrival at l_{21} will apply. The actual utility of executing $plan^*$ is

$$U^l(plan^*) = \exp(-\lambda \sum_{j=1}^2 T_{j-1,j}) [a_{11}^\alpha \exp(-\gamma_1 T_w) + \exp(-\gamma_2 T_w)] \quad (22)$$

where $\exp(-\gamma_1 T_w)$ represents the penalty of waiting time at l_a , since we handle waiting time as early arrival. With I_{wait} , the individual has two options: 1) still using l_{11} for g_1 but starting earlier; 2) switching to l_{12} . For option 1) (see Figure 6(a)), the individual can avoid the late arrival at l_{21} but still have to go through the waiting time T_w . Thus, the utility of this new plan $plan_{new1}$ is

$$U^l(plan_{new1}) = \exp(-\lambda \sum_{j=1}^2 T_{j-1,j}) [a_{11}^\alpha \exp(-\gamma_1 T_w) + 1] \quad (23)$$

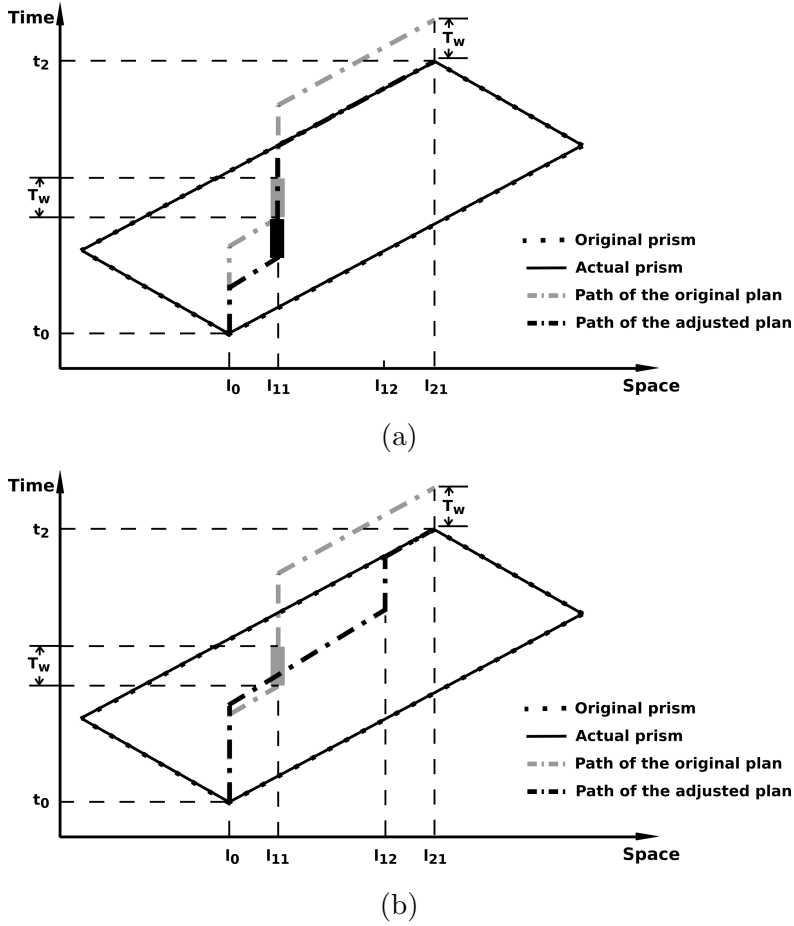


Figure 6. The adjusted plans based on the waiting time information: (a) starting earlier from l_0 but still choosing l_{11} for g_1 ; (b) using l_{12} for g_1 . Note that in both (a) and (b), the actual prism overlaps with the original prism since the spatiotemporal properties of the fixed task g_2 do not change.

For option 2) (see Figure 6(b)), the individual can avoid the waiting time at l_{11} , and can arrive at l_{21} on time. However, since l_{12} has a lower capability to support task g_1 compared with l_{11} , we will obtain another utility value for $plan_{new2}$

$$U'(plan_{new2}) = \exp(-\lambda \sum_{j=1}^2 T_{j-1,j}) (a_{12}^\alpha + 1) \quad (24)$$

In this situation, we need to compare the utilities of the two candidate plans, and the utility of the new optimal plan will be the maximum of the two (equation (25)). The value of I_{wait} can then be calculated using $U'(plan_{new}^*) - U'(plan^*)$.

$$U'(plan_{new}^*) = \max\{U'(plan_{new1}), U'(plan_{new2})\} \quad (25)$$

6. Simulation on a transportation network

In this section, we conduct a simulation using the proposed framework on a real-world transportation network from the city of Santa Barbara, California, USA. Specifically, we simulate a scenario in which an individual needs to first have breakfast (g_1) and then attend a workshop (g_2). This scenario is similar to the example used in Raubal *et al.* (2004).

For g_1 , the individual can choose among three candidate locations, l_{11} , l_{12} , and l_{13} , whose capabilities to support g_1 are defined as 1, 0.8, and 0.6 respectively in this simulation. For g_2 , it has a fixed location l_{21} whose capability to support g_2 is 1, and a fixed PAT t_2 . Based on the two tasks, we measure the relative values of four different information items, and assign them priorities. The four information items are: (1) $I_{traffic}$, which informs the individual about the congestion on a segment of Highway 101 that costs about 30-minute delay; (2) $I_{location}$, which notifies the individual about the location change of the workshop from l_{21} to l'_{21} ; (3) I_{wait} , which informs the individual that a queue is waiting at l_{11} which may cost additional 15 minutes; (4) $I_{temperature}$, information about the current temperature, which is assumed to have no influence on the spatiotemporal properties of the tasks. We add $I_{temperature}$ into this simulation because intuitively it should be assigned the lowest priority since it does not contribute to the task planning. Therefore, it could help examine the simulation result. Figure 7 shows an overview of the simulation.



Figure 7. An overview of the simulation scenario.

The parameters in the proposed framework has been configured as in Table 1. The values of α and β are based on the space-time accessibility study by Ettema and Timmermans (2007). The values of λ , γ_1 , and γ_2 are based on a human participant study by Small (1982), in which a survey was conducted on 527 daily commuters to find out their opinions on travel time as well as early and late arrivals to work. While these values are consistent with our general expectations (e.g., late arrival is generally expected to have stronger consequences than early arrival, and thus γ_2 should be larger than γ_1), they could be more accurately estimated based on the particular applications and targeted users. In this simulation, however, our goal is to demonstrate the effectiveness of the framework on a real-world transportation network. Therefore, we rely on the parameters derived from the literature instead of deriving new values.

Table 1.: The parameter configuration for the simulation.

Parameter	Description	Value
α	The penalty parameter on a location which cannot fully meet the task requirements	1
β	The penalty parameter for not being able to stay enough time at a location to complete the task	1
λ	The penalty parameter for travel time	0.106
γ_1	The penalty parameter for schedule delay early (<i>SDE</i>)	0.065
γ_2	The penalty parameter for schedule delay late (<i>SDL</i>)	0.254

To measure the relative values of the four information items, we follow the workflow presented in section 4.3. We start by finding the optimal plan $plan^*$ when no information is given. In that situation, $plan^*$ can be identified by considering the total travel time, the capabilities of l_{11} , l_{12} , and l_{13} in supporting g_1 , and the potential penalties that may apply. Dijkstra's algorithm has been used to find the route that costs the minimum amount of travel time on the road network. We employ Dijkstra's algorithm because our simulation is based on ArcGIS 10.2 which has already implemented it as a shortest path function. Other algorithms, such as A^* , could achieve better efficiency by including heuristics, and therefore could also be used. The utilities of the three different plans are calculated using equation (12), and the result is summarized in Table 2. Figure 7 visualizes the routes of the plans. Without any additional information, the individual may choose $plan_1$ since this plan seems to provide the highest utility U . However, by executing such a plan, the individual will run into the traffic congestion, spend time waiting at l_{11} , and most importantly, she will arrive at the wrong location for the workshop. Consequently, the actual utility U' of executing $plan_1$ becomes 0.

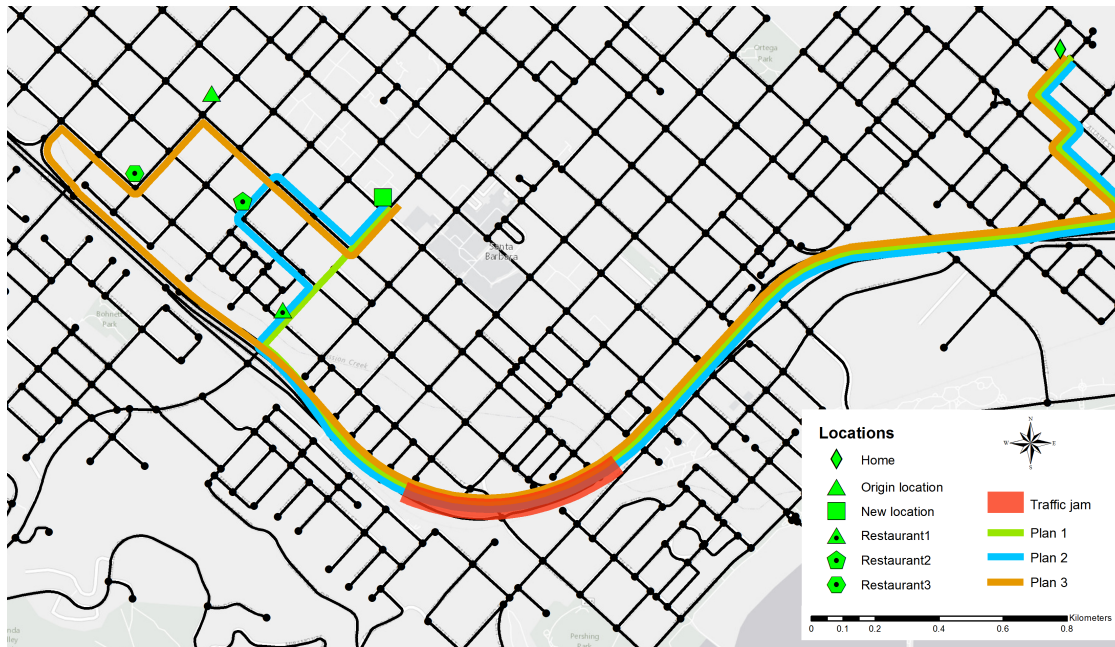
Table 2.: Simulation result when no information has been provided. Variables without the prime (e.g., U) represent the values that the individual thinks the plan could achieve, while those with the prime (e.g., U') represent the values the plan actually achieves. The unit for time variables is minute.

Plan	Travel time		Task g_1			Task g_2			Utility	
	T	T'	Loc	T_{wait}	T'_{wait}	Loc	T_{late}	T'_{late}	U	U'
$plan_1$	6.01	36.01	l_{11}	0.00	15.00	l_{21}	0.00	45.00	1.17	0.00
$plan_2$	6.01	36.01	l_{12}	0.00	0.00	l_{21}	0.00	30.00	0.95	0.00
$plan_3$	6.03	36.03	l_{13}	0.00	0.00	l_{21}	0.00	30.00	0.84	0.00

In the next step, we calculate the utility improvements that can be introduced by the four information items respectively. $I_{traffic}$ and I_{wait} can inform the individual about the traffic congestion and the approximate waiting time at l_{11} , and therefore the individual can adjust her plans to reduce the potential penalties. However, the individual will arrive at the wrong location for g_2 , and the plans will then become invalid. Consequently, the utility improvements brought by these two information items become 0. Given $I_{temperature}$, the individual will not change her original plan (i.e., $plan_1$ in Table 2), since this information does not influence the spatiotemporal properties of the tasks. When $I_{location}$ is provided, the individual will be informed about the correct location for g_2 , and therefore can change her plan accordingly. Although the individual may still run into the traffic congestion and spend time waiting, the plans will become valid. We simulated these situations with each of the four information items provided, and the simulation result given $I_{location}$ is summarized in Table 3. The adjusted routes given $I_{location}$ are visualized in Figure 8.

Table 3.: Simulation result when $I_{location}$ has been provided.

Plan	Travel time		Task g_1			Task g_2			Utility	
	T	T'	Loc	T_{wait}	T'_{wait}	Loc	T_{late}	T'_{late}	U	U'
$plan_1$	5.03	35.03	l_{11}	0.00	15.00	l'_{21}	0.00	45.00	1.06	0.01
$plan_2$	6.36	36.36	l_{12}	0.00	0.00	l'_{21}	0.00	30.00	0.92	0.02
$plan_3$	7.48	37.48	l_{13}	0.00	0.00	l'_{21}	0.00	30.00	0.72	0.01

Figure 8. The routes of the plans when $I_{location}$ is provided.

It can be seen that the individual may choose $plan_1$ since it provides the highest U . When $plan_1$ is executed, it achieves 0.01 for U' . As we have mentioned earlier, this small value does not provide direct meaning, and should be interpreted by comparing with the values of other information items. Since the others only achieve 0 in terms of utility improvement, $I_{location}$ should be assigned the highest priority. Consider a smartwatch that can display only one information item each time. $I_{location}$ should be the most important information that needs to be first shown to the user.

We then evaluate the priorities of the three other information items. The current optimal plan is $plan_1$ in Table 3, which achieves 0.01 for U' . When $I_{traffic}$ is provided, the individual can adjust her plans to avoid the congestion, and this simulation result is summarized in Table 4. As can be seen, the individual will choose $plan_1$ given $I_{traffic}$, since it provides the highest U . The U' of $plan_1$ is 0.22, and therefore the utility improvement introduced by $I_{traffic}$ is $0.22 - 0.01 = 0.21$. Given I_{wait} , the individual can adjust her plans accordingly, and this simulation result is summarized in Table 5. In this situation, the individual will choose $plan_2$ with the highest U . When $plan_2$ is executed, however, the individual will face the traffic congestion, and will achieve a U' 0.02. As a result, the utility improvement introduced by I_{wait} is $0.02 - 0.01 = 0.01$. When $I_{temperature}$ is provided, the individual will still execute the original $plan_1$ in Table 3, and the utility improvement introduced by $I_{temperature}$ is $0.01 - 0.01 = 0$. Thus, $I_{traffic}$ should be the most important information in the second iteration.

Table 4.: Simulation result when $I_{traffic}$ has been provided in addition to $I_{location}$.

Plan	Travel time		Task g_1			Task g_2			Utility	
	T	T'	Loc	T_{wait}	T'_{wait}	Loc	T_{late}	T'_{late}	U	U'
$plan_1$	5.60	5.60	l_{11}	0.00	15.00	l'_{21}	0.00	15.00	1.10	0.22
$plan_2$	6.68	6.68	l_{12}	0.00	0.00	l'_{21}	0.00	0.00	0.89	0.89
$plan_3$	7.99	7.99	l_{13}	0.00	0.00	l'_{21}	0.00	0.00	0.69	0.69

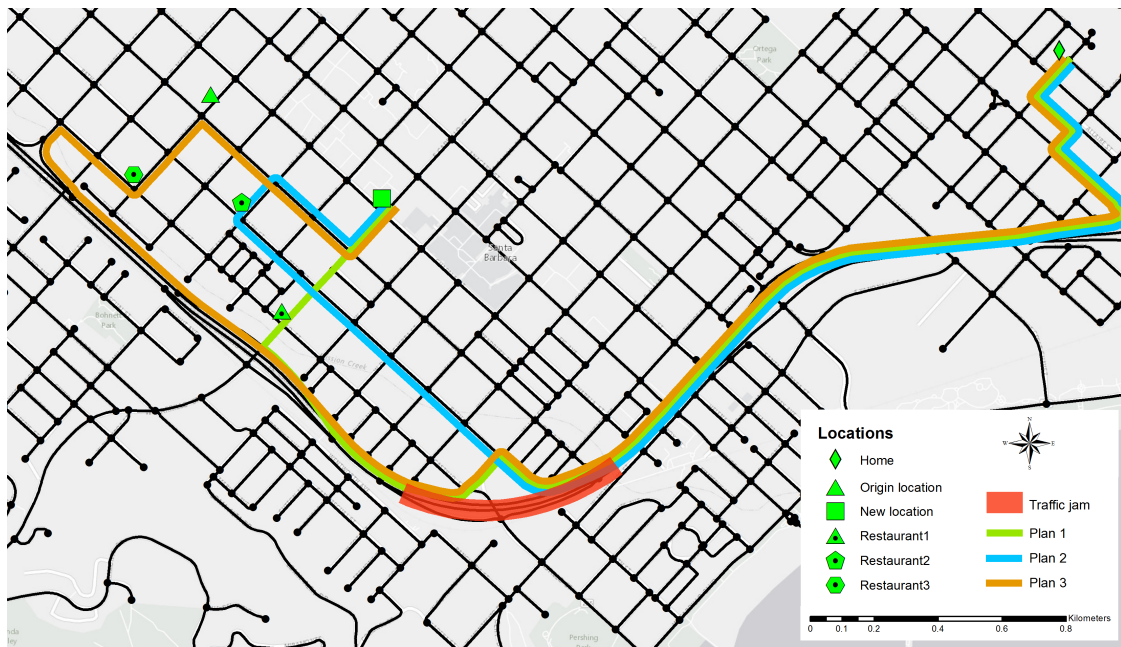
Table 5.: Simulation result when I_{wait} has been provided in addition to $I_{location}$.

Plan	Travel time		Task g_1			Task g_2			Utility	
	T	T'	Loc	T_{wait}	T'_{wait}	Loc	T_{late}	T'_{late}	U	U'
$plan_1$	5.03	35.03	l_{11}	15.00	15.00	l'_{21}	0.00	30.00	0.81	0.01
$plan_2$	6.36	36.36	l_{12}	0.00	0.00	l'_{21}	0.00	30.00	0.92	0.02
$plan_3$	7.48	37.48	l_{13}	0.00	0.00	l'_{21}	0.00	30.00	0.72	0.01

We continue with the third iteration on I_{wait} and $I_{temperature}$. The current optimal plan is $plan_1$ in Table 4 which achieves a U' of 0.22. Given I_{wait} , the simulation result is summarized in Table 6. Since the individual is now aware of all the adverse conditions, she can take the best strategy to avoid these penalties. As a result, the individual will choose $plan_2$ in Table 6, which achieves a U' of 0.89. Thus, the utility improvement introduced by I_{wait} is $0.89 - 0.22 = 0.67$. The utility improvement introduced by $I_{temperature}$ is $0.22 - 0.22 = 0$. Figure 9 visualizes the final routes of the plans.

Table 6.: Simulation result when I_{wait} has been provided in addition to $I_{location}$ and $I_{traffic}$.

Plan	Travel time		Task g_1			Task g_2			Utility	
	T	T'	Loc	T_{wait}	T'_{wait}	Loc	T_{late}	T'_{late}	U	U'
$plan_1$	5.60	5.60	l_{11}	15.00	15.00	l'_{21}	0.00	0.00	0.76	0.76
$plan_2$	6.68	6.68	l_{12}	0.00	0.00	l'_{21}	0.00	0.00	0.89	0.89
$plan_3$	7.99	7.99	l_{13}	0.00	0.00	l'_{21}	0.00	0.00	0.69	0.69

Figure 9. The routes of the adjusted plans after $I_{location}$, $I_{traffic}$, and I_{wait} have been provided.

Based on the simulation result, the priorities of the four information items should be

$$I_{location} > I_{traffic} > I_{wait} > I_{temperature}$$

7. Conclusions and future work

Information has been recognized as a valuable resource in our everyday life. The value of information, however, depends on not only the information itself but also the tasks in which the information will be used for decision making. Therefore, the same information item may have different values with regard to different tasks. Recent years have witnessed a fast expansion in the volume of information, the emergence of small-screen mobile devices, and an increasingly rapid pace of life. In this context, there exists a demand for assisting individuals in identifying useful information to complete their tasks. This paper presents a theoretical framework for task-oriented information value measurement. Such a framework integrates information value theory and the space-time prism, and can evaluate the priorities of multiple information items based on their capabilities of improving task planning. We develop and formalize this framework by extending the utility functions traditionally used in space-time accessibility studies, and illustrate this framework using a simplified example in time geography. A simulation has been conducted to demonstrate the applicability of the proposed framework on real-world transportation networks. This research could be used to improve information display on the fast-developing wearable devices, such as smartwatches. Meanwhile, this framework could also help provide more personalized information services based on individuals' tasks. A potential data source for identifying the tasks of an individual is digital calendars (e.g., Google Calendar) where individuals can record the spatiotemporal properties of important tasks.

This research, however, is still a first step towards task-oriented information value measurement, and can be extended in several future directions. First, our framework currently employs the same set of penalty parameters for different tasks. While there exists some consistence in people's attitudes towards time, the penalties could vary between tasks. For example, being late for a workshop may have a different consequence than being late for work. Thus, specifying parameters in a finer granularity with regard to different task types could help enhance the proposed framework. Second, our work assumes that the information items can be directly associated with the corresponding spatiotemporal properties of the tasks. More research is still necessary to make such association process automatic or semi-automatic. Finally, the presented research examines the case in which information items are received before the tasks begin. It would also be interesting to study the values of information items as they are received during a task. Semantic trajectories (Hu *et al.* 2013) of individuals, with information on the places they visited or plan to visit, the used transportation modes, and so forth, could provide additional contexts for measuring information value.

Acknowledgement

The authors would like to thank Helen Couclelis for her constructive suggestions.

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