DOES EN-ROUTE INFORMATION IMPROVE ROAD NETWORK PERFORMANCE? AN EXPERIMENTAL STUDY OF THE ONLINE INFORMATION PARADOX

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ABSTRACT

This study investigates the empirical presence of a theoretical transportation paradox, defined as the "Online Information Paradox" (OIP). The paradox suggests that the provision of online information deteriorates trip conditions for the entire network relative to the scenario where information is not provided to users. The analytical presence of the paradox was derived for the specific network structure by using two equilibrium models, the first being the Expected User Equilibrium (EUE) solution (no information) and the other being the User Equilibrium with Recourse (UER) solution (with information). A laboratory economic experiment is used to involve an incentivized computerized route choice game that investigates the physical presence of the paradox.

Aggregate statistics of path flows and Total System Travel Cost (TSTC) were used to compare the experimental results with the theoretical findings. A total of 12 groups of 12 participants completed the experiment and the OIP was observed in 11 of the 12 cases, its occurrence being highly significant. Though information increased travel costs for users on average, it reduced the volatility of travel costs experienced in the no information scenario indicating that information can achieve a more reliable system. Further replications of such experiments and more importantly field based identification of the phenomena will force transport professionals to not only be aware of the emergence of the paradox but also emphasize the need for the adoption of adaptive traffic assignment techniques such as UER to appropriately model the acquisition of information on a road network.

Keywords: Information, Paradox, Network Performance, Adaptive Routing, Experimental Economics

1 INTRODUCTION

Traffic congestion is a problem affecting most metropolitan areas throughout the world resulting in significant economic, social and environmental costs. Alleviating congestion has been and still is a major focus for traffic engineers and transport planners. An initial solution to the problem was investment into the construction of transportation infrastructure, to provide increased capacity within the network, allowing users additional routes to travel to their destinations. Braess in 1968 *(1)* presented analytically that the construction of an additional link which connects two alternative routes between an origin and destination pair may increase the travel cost for all users of the network. This result is known as the Braess Paradox and has been shown to be empirically relevant by Rapoport et al. in 2009 Rapoport et al. *(2)* and Morgan et al in 2009 Morgan et al. *(3)* using methods of experimental economics in a controlled laboratory setting.

The emergence of the Braess Paradox and of other capacity paradoxes (such as the Down-Thomson Paradox *(4)*) has forced transport professionals to consider additional measures, other than increasing capacity, to reduce congestion within networks. One approach is to focus on traffic management practices to better utilize current infrastructure in an attempt to avoid congestion events. The provision of information to network users has been a recent initiative through the advent of GPS technology and the development of Intelligent Transportation Systems. In particular, Advanced Traveler Information Systems (ATIS) have been implemented across the last decade to provide travelers with information about network conditions. The intention of these systems is to reduce the uncertainties of travel and as a result improve decision making by the user, benefitting the user as well as the system as a whole. For example, travelers can be informed of disruptions on the road network; those affected by the disruption may decide to alter their route choice saving time at an individual level potentially leading to a positive system wide impact. Chorus et al. *(5)* presents a detailed review of a number of analytical and simulation based research efforts that have investigated the impact of information on congested networks which support the notion that information provision improves performance. However there have been a few studies suggesting that the provision of incomplete or imperfect information regarding route capacities and travel times could lead to a deterioration of performance *(6-9)*.

It is clear that the implementation of these systems affects the behavior and travel patterns of road users. Accordingly, it is essential for planning models to account for these behavioral implications leading to a number of research efforts *(10-14)*. A static equilibrium model which incorporates the impact of information on traffic assignment is User Equilibrium with Recourse (UER) *(14)*. UER advances the concept of traditional User Equilibrium (UE) to consider en-route decision making in light of information sources within a network. The paper presents the analytical existence of a "Braess Paradox" of Information, henceforth termed the "Online Information Paradox" (OIP), where the provision of information increases the total system travel cost questioning the viability of the information system. This paradox has only been presented theoretically and it is essential to investigate the phenomenon in a physical setting. The occurrence of the paradox in a controlled laboratory experiment should implore transport planners and engineers to further evaluate the costs and benefits of en-route information for managing transportation networks, highlighting the importance of the research. Accordingly, the focus of this study is to investigate the OIP presented in the UER framework. An experiment involving an incentivized computerized route choice game was designed to understand the route choice behavior of participants under two information regimes: a base level treatment defined as the "No Information" case and a scenario with full perfect information, defined as "Information" case. Empirical data related to path utilization and total system travel costs were extracted from the experiment to compare with theoretical equilibrium solutions and also identify the presence of the paradox in a physical setting.

2 BACKGROUND

Ben-Elia and Avineri (2015) presents the latest review of behavioral research associated with travel information Ben-Elia and Avineri *(15)*. The comprehensive review of research conducted across the last decade indicates that information could assist individuals in coping with uncertainty though the benefits on a network wide scope are debatable. Researchers have proposed potential adverse effects that can be a result of information provision as follows *(7, 15-18)*;

- Oversaturation: The volume of information exceeds the cognitive capabilities of the individual and as such results in decision making that do not correlate with the information provided.
- Concentration and Overreaction: Travelers all acquire the information and make identical decisions, thus moving congestion from one location of the network to the other.

In general, there have been a number of studies that have investigated the provision of information and the impact on network performance. The studies which have been conducted are either experiment based or field observations. This particular study relates to the empirical observance of a paradox. Thus, the remainder of the literature review will focus on studies conducted in the experimental economics domain related to information dissemination and traffic paradoxes in addition to a discussion of the traffic assignment method that underpins the Online Information Paradox.

2.1 Application of Experimental Economics in Transportation

Laboratory experiments have been used in studying driving behavior as well as some specific equilibrium models and paradoxes *(19-23)*. A complete review of the application of experimental economics within the field of transportation is detailed in Dixit et al. (2015) highlighting the strengths and weaknesses of the approach *(24)*.

During the past decade a number controlled laboratory experiments have been conducted on the traditional Braess Paradox *(2, 25-27)* and the Downs Thomson Paradox *(3)*. Rapoport et al. presented the results of experiments investigating the Braess Paradox *(2, 26, 27)*. These studies involved simulated route choice games using networks susceptible to the Braess Paradox in a controlled laboratory environment. Rapoport et al. (2006) Rapoport et al. *(27)* and Rapoport et al. (2009) Rapoport et al. *(2)* confirmed the presence of the Braess paradox and suggested that with learning and experience the paradox would be further exacerbated. Recently, there have been two experiments that have specifically investigated the impact of pre-trip information on route choice by Rapoport et al (2014) and Knorr et al (2014) *(8, 28)*. Both these studies investigated decisions in a controlled laboratory environment utilizing networks with two alternative congestible routes which vary unpredictably. Knorr et al. (2014) suggests that the provision of information to the entirety of the demand does not yield significant benefits to any individual traveler. Rapoport et al. (2014) presents an experiment designed to examine the work of Lindsey et al. (2014) *(29)*. The findings of the study were consistent with the paradoxical findings of the theoretical model presented by Lindsey et al. (2014) suggesting that information is detrimental when conditions on both routes are perfectly correlated whilst information is beneficial when uncorrelated.

The most relevant research to this study are investigations into real-time online information by Lu et al. (2012) *(30)* and a follow up study by the same team Lu et al. (2014) *(31)*. Similar to this study, Lu et al. (2012) *(30)* conducted an experiment where participants faced a 3 route network and with the possibility of an incident occurring on one of the routes. As with this study, treatments with and without descriptive online information provided at a downstream node were assessed to understand the impact of information. In addition, the impact of providing information about past performance of the entire network, “the foregone payoff” was also investigated. The findings of the study show that information reduces the overall network travel time and increases travel time reliability. However, benefits of information provision depreciate when details of the foregone alternative were revealed to participants. The follow up study conducted in 2014 by Lu et al. considered a greater sample size and also considered the case of providing feedback on subsequent rounds regarding only the chosen alternative. Similar positive results were obtained regarding the provision of information. Furthermore, 90% of the participants chose to travel on the paths that would provide them information of network conditions. This suggests that the concentration and overreaction phenomena are possible, as it is clear that travelers desire information within a road network, creating impetus for the investigation of the theoretical OIP. In addition to studying a specific analytical paradox where information deteriorates travel conditions, there are notable differences in the experimental methodology between this study and the studies conducted by Lu et al. *(30, 31)*. The primary difference is that the previous studies used a fixed incentive scheme while this study uses performance based incentives abiding by the principles of experimental economics. Overall, these studies provided incredible insight into the application of online information based experiments, imperative for the formation of this research project.

2.2 User Equilibrium with Recourse

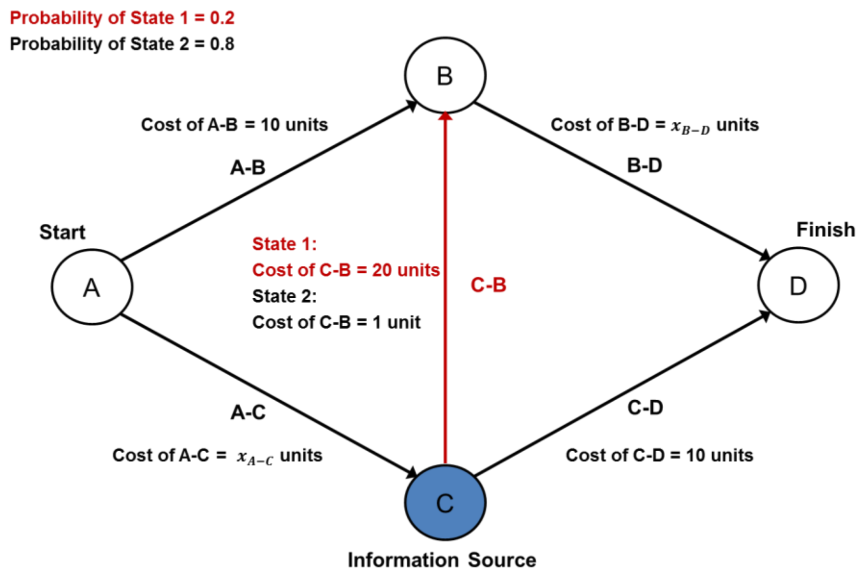
Traditional equilibrium traffic assignment models, such as deterministic user equilibrium (UE), assume that users deterministically choose minimum cost paths, and then remain on that path regardless of realized network conditions. Accordingly, these approaches do not account for adaptive behavior. In contrast, User Equilibrium with Recourse (UER) incorporates road users' en-route decision making in the presence of information regarding the state of the network. The reader is referred to the paper by Unnikrishnan and Waller (2009) Unnikrishnan and Waller *(14)*, where UER is introduced and discussed in detail, including mathematical formulations; this work contains only a brief description to assist in presenting what is described as a "Online Information Paradox" (OIP) observed within the equilibrium model.

UER is a static equilibrium model that accounts for one-step local information and user recourse on account of gaining that information *(14)*. An important assumption in the formulation is that the link cost functional forms are known but the link capacities are uncertain prior to departure. Only upon reaching an upstream node does a user begin to gain information about the capacity state of the following link. Thus, in a UER scenario, each link of a network could possess multiple "traffic states" with a probability of occurrence. Depending on the state of the link, which is disseminated through a source of information (Variable Message Sign, ITS technology), a user would choose the next link to travel on to reach his or her destination. To account for users' response to different traffic states, UER considers a selection of possible hyper-paths known as routing policies instead of the least cost path *(32)*. Accordingly, a network considering user recourse is in equilibrium when, *"the expected cost of all used routing policies is minimum and equal and no user can unilaterally change their routing policies to improve the experienced expected cost"*. The paper further provides a demonstration of the user recourse equilibrium, considering a set of specific link costs and states, suggesting that the provision of information can result in a flow pattern that increases the travel costs of each user and consequently for the system as a whole. This paradoxical phenomenon (defined in this paper as OIP) was discussed in Section 3.4, "Braess Paradox: Model A" within Unnikrishnan and Waller (2009) *(14)* and a similar example is used for the basis of this study and presented in Section 3.

3 THE ONLINE INFORMATION PARADOX (OIP): EXPERIMENTAL DESIGN

3.1 Experimental Context

The treatments of the experimental design were based on the following example of the OIP. Figure 1 presents the network, link states and the associated link costs considered. The network services 12 units of demand travelling between origin node *A* and destination node *D*. Users travel along one-way links with the possibility of using three competing routes, *A-B-D*, *A-C-B-D* and *A-C-D*. If a user travels on link *A-B*, there is no option to alter the route in reaching the destination *D*. However, if a user selects link *A-C* there is the possibility of using link *C-B* and *B-D* to reach *D* or using link *C-D* to directly reach *D*. Thus, the users who initially selected link *A-C* can adapt their route depending on the prevailing traffic conditions of link *C-B* or link *C-D* if they are provided information at node C. The paradox compares the results of the User Equilibrium with Recourse traffic assignment model with and without the presence of perfect information. The information provided at node *C* is related to the state of link *C-B*, where 20% of the time the cost of using link *C-B* is equal to 20 units and the remaining 80% of the time the cost of using link *C-B* is equal to 1 unit. All other links within the network have a single state with no variation in cost functions as presented in Figure 1. This scenario is analogous to road *C-B* experiencing a disruption such as an accident or breakdown during State 1 which results in the closure of lanes and the increase of travel cost for all users.



Link	Link No.	State	Probability	Cost Function
(A-B)	1	1	1	10
(A-C)	2	1	1	x_{A-C}
(B-D)	4	1	1	x_{B-D}
(C-B)	3	1	0.2	20
(C-B)	3	2	0.8	1
(C-D)	1	1	1	10

Figure 1: Online Information Paradox Network: Link States and respective cost functions

3.2 Theoretical Equilibrium Conditions

The theoretical equilibrium conditions were calculated to compare with the results of the experiment using the following models;

- Expected User Equilibrium (EUE);
- User Equilibrium with Recourse (UER);

The EUE approach is similar to the traditional User Equilibrium (UE) approach as it considers the minimization of all utilized path travel costs *(33)*. However, instead of considering separate equilibrium conditions for each traffic state, EUE considers the expectation of link costs to account for the uncertainty. This model assumes that users experience the different states of the network; however instead of having perfect knowledge of the realization of each state, the users develop an understanding of the average travel conditions[1]. In relation to the assessment of the OIP this model serves as a representation of the no information case. The lack of information results in non-adaptive behavior. Travelers on link *A-C* are not aware of the traffic conditions of either link *C-D* or link *C-B* and accordingly consider expected costs to determine the minimum cost path. Thus, under the no information case, for 12 units of demand, the EUE solution decomposes to the UE solution where demand is split evenly across path *A-B-D* and *A-C-D*, assuming expected link costs and the solution is presented in Table 1(a).

Table 1: Analytical equilibrium conditions: (a) Expected User Equilibrium (EUE) Traffic Conditions, (b) User Equilibrium with Recourse (UER) Traffic Conditions

(a)

EUE Conditions (No Information)		
Path	**Flow**	**Path Cost**
ABD	6	16
ACBD	0	16.8
ACD	6	16
Total System Travel Cost (TSTC)		**192**

(b)

UER Conditions (Information)									
Policy Statistics					**Path Statistics**				
Policies	**State 1 Path**	**State 2 Path**	**Policy Flow**	**Policy Cost**	**Path**	**State 1 Flow**	**State 1 Cost**	**State 2 Flow**	**State 2 Cost**
P1	A-B-D	A-B-D	4	18	ABD	4	14	4	19
P2	A-C-B-D	A-C-B-D	0	20.8	ACBD	0	32	5	18
P3	A-C-B-D	A-C-D	0	20.8	ACD	8	18	3	18
P4	A-C-D	A-C-D	3	18					
P5	A-C-D	A-C-B-D	5	18					
Total System Travel Cost (TSTC)			**216**						

In order to determine the equilibrium solution for the "Information" case, the UER solution is calculated *(14)*. The five routing policies which an individual would consider in this example are:

- Policy 1 (P1): State 1 Path: **A-B-D**, State 2 Path: **A-B-D**
- Policy 2 (P2): State 1 Path: **A-C-B-D**, State 2 Path: **A-C-B-D**
- Policy 3 (P3): State 1 Path: **A-C-B-D**, State 2 Path: **A-C-D**
- Policy 4 (P4): State 1 Path: **A-C-D**, State 2 Path: **A-C-D**
- Policy 5 (P5): State 1 Path: **A-C-D**, State 2 Path: **A-C-B-D**

The core assumption of this traffic assignment technique is that all users arriving at an upstream node observe the same link states for all outbound links. This means that the state of each link is static throughout the assessment, for the entirety of the demand traversing the network. This is parallel to an incident disrupting traffic for a period of time or the presence of sustained peak period

[1] An important assumption is that transport users are risk neutral.

congestion in a portion of a network. The UER solutions calculated for this example indicate that 4 units of demand select *P1*, 3 units select *P4* and 5 units select *P5*, as shown in Table 1(b).

Comparing the case where no information is provided (Table 1(a)) with the case where information is provided (Table 1(b)), it is clear that individual travel costs and system performance depreciates as a result of information provision. Travel cost for the individual increased from 16 to 18 and total system travel cost increased from 192 to 216 highlighting the caution required when implementing information systems within road networks.

3.3 Experiment Conditions

3.3.1 Computerized Route Choice Game Treatments

A computerized route choice game served as the core element of the experiment. The experiment was programmed and conducted using software specifically designed for the application of economic experiments, zTree *(34)*. The game replicated the network properties and demand conditions described in subsection 3.1. Participants divided into groups of 12, where each participant represented a unit of demand, played the role of motorists who repeatedly had to travel between a specified origin (*A*) and destination (*D*). As presented in the example, the participants had a choice of 3 routes, *A-B-D*, *A-C-B-D* and *A-C-D*. At the completion of each decision period, the traffic conditions experienced by all the participants were revealed to each participant prior to making the next routing decision. The state of the link *C-B* was determined randomly through z-tree but satisfied the likelihood of occurrence of 20% for State 1 and 80% for State 2, this means that each group faced State 1 conditions in 4 out of the 20 periods for each treatment, as the network game was repeated across 20 rounds for each treatment (within subject design). The purpose of divulging personal and network performance of each journey was to capture any learning effects across both information regimes. Even though there is a unique equilibrium solution for both the no information (EUE) and full information (UER) treatments, there are numerous ways the participants can arrange themselves to achieve the equilibrium solution. Take for example the no information case; the EUE solution indicates that route *A-B-D* and route *A-C-D* will contain 6 units of demand each. The participants have 924 (C(12,6)) different combinations of achieving this flow pattern with only the history of the previous periods performance and without any communication with other participants presenting a very complex coordination problem *(2, 8, 22)*. Based on the difficulty of the task, achieving equilibrium flow patterns on average is a significant observation. In order to investigate the presence of the OIP, two treatments were carried out;

- ***Treatment 1***: No Information provision
- ***Treatment 2***: Information provided at Node C regarding the prevailing traffic conditions on link C-B

Participants traversed a network that was similar to Figure 1. The only difference being that instead of referring to the traffic state of Link *C-B* as “State 1” and “State 2”, the route selection was placed in the context of an incident occurring on Link *C-B*. State 1 referred to “Incident” conditions and State 2 referred to “No Incident” conditions on Link *C-B*. This contextualization was undertaken to place participants in a realistic driving scenario that they may face on their daily commutes. The method in which participants selected a route varied based on the treatment. Treatment 1, involved no provision of information, this meant that each participant selected the entirety of the route from origin *A* to *D*. Treatment 2 included the provision of information at node *C*, as a result participants performed the route selection in a staged manner on a link by link basis.

3.3.2 Additional tasks and incentive structure

Additional tasks were undertaken to gather information of the characteristics of each of the participants to better understand individual decision making. Participants completed a multiple price lottery (MPL) task to gain information about their risk attitudes prior to completing the computerized route choice tasks*(35, 36)*.*(35)*. After completing the route choice tasks, participants were asked to fill out a short 10 minute socio-demographic questionnaire. It must be emphasized that the focus of this particular paper was the observation of the OIP at an aggregate level and as such the analysis of additional task data will not be detailed within this paper.

A key aspect of experimental economics is incentivization to ensure that the participants' decisions had realistic consequences. Incentives for this experiment involved a static participation fee of AUD$5 and performance based reward surrounding the multiple price lottery and each of the computerized route choice tasks. In terms of the route choice tasks, each participant received an income of 45 units for each of the periods of both tasks. The payoff for a round was calculated by deducting the travel cost experienced by the participant from the initial income. At the end of both treatments, a random period from each task was selected and the payoff associated with that round was paid to the participant, where every unit equaled AUD$0.25. On average, a participant could approximately earn $25 across the session.

The route choice tasks involved repeated decision making which can result in participant fatigue affecting decision making and ultimately the results of the experiment. Accordingly, a pilot test was conducted to assess the number of feasible periods that could be played by a participant. A group of 12 colleagues from the Research Centre for Integrated Transport Innovation at the University of New South Wales (UNSW) participated in the pilot study and were asked to provide feedback on the length of the experiment and comment on how many periods should be put in place. The pilot study was conducted over 2 hours, where 20 rounds of each task were completed. The participants revealed that this length of time and number of periods neared the limits of their cognitive capabilities and that anymore periods would be a strain for the participant. It is acknowledged that the number of periods used for this experiment is significantly lower than that conducted recently by Knorr et al. (2014) and Rapoport et al. (2014), which used 50 rounds per treatment and 80 rounds per treatment respectively *(8, 28)*. However, these experiments involved a decision between 2 routes as compared to the 3 routes considered in this study, reducing the cognitive load on the participant. Furthermore, the information task involved staged decision making based on the acquisition of online information which increases the time taken to complete each round. Based on these key differences, and the findings of the pilot study it was decided that the participants should undertake 20 periods of each treatment.

3.3.3 Recruitment Process and Experimental Procedure

Participants were recruited using the UNSW Australian School of Business (ASB) Experimental Research Laboratory. Admission to participate in the study was contingent on respondents being at least 17 years old to ensure that participants understood the meaning of route choice in a real driving scenario. The laboratory used for the experiment contained computer workstations with enough space between participants to prevent collusive activities. Each session consisted of a total of 24 participants who were randomly separated into 2 groups of 12 participants to complete the route choice tasks. The procedure of the experiment can be summarized as follows;

1. Participants completed the MPL task.
2. Participants completed the computerized route choice tasks across both Treatment 1 and Treatment 2.
3. Participants completed the demographic questionnaire.
4. Participants' payoffs were calculated and each participant was paid.

To control for order effects the sequence of the treatments were varied across the sessions. The experiments with the following sequences of tasks were conducted across different sessions.

- Order 0: MPL Task; Treatment 1 (No Information, 20 periods), Treatment 2 (Information, 20 periods), Questionnaire.
- Order 1: MPL Task; Treatment 2 (Information, 20 periods), Treatment 1 (No Information, 20 periods), Questionnaire

Six sessions of the experiment were held during September and October 2015 (Sessions 1 to 3 undertook Order 0, while Sessions 4 to 6 undertook Order 1 described above). Each session involved 24 participants thus obtaining data from a total of 144 participants. There was a balance between genders with 47% of the participants being male and 53% female. More than 68% of the participants had greater than one year's experience in driving a vehicle suggesting that there was a certain level of understanding in relation to route choice and driving. Given that the participants were recruited from a University staff and student pool, it is acknowledged that the average age of the participants is young at 22.14 years. However, it should be noted that 22% of the participant pool were above the age of 24 indicating that this study did not focus exclusively on undergraduate student behavior, obtaining a degree of diversity.

4 RESULTS AND ANALYSIS

Each round of the computerized route choice game provided a traffic assignment pattern (1 observation) which could be compared with the theoretical equilibrium results. Since each session consisted of two groups of 12 participants a total of 40 observations were recorded for each treatment. Therefore, across the six sessions conducted, there were 240 observations for each treatment. The data obtained was statistically analyzed to compare with the predictions of the theoretical models and identify the presence of the OIP. The key performance metrics assessed were path utilization across the three routes and the Total System Travel Cost (TSTC) which describes the system wide performance of the network.

Table 2 presents a comparison of the analytical path flow solutions calculated in subsection 3.2 and the observed mean path flow results from the experiment. The EUE solution depicting the "No Information" case suggested that there will be a 50% split of the demand on route *A-B-D* and *A-C-D*, and zero usage of *A-C-B-D*. The observed mean flows differ from this solution, with a mean flow of 1.788 on path *A-C-B-D*. On average, across the entire data set there were 1 to 2 participants who selected *A-C-B-D*. This can be explained by individuals hoping that State 2 conditions would prevail and they would be able to significantly reduce their travel cost by encountering the 1 unit cost on link *C-B*. This tends to suggest that the EUE solution is not capturing the behavior of users in the no information case. However, it should be noted that across the last 2 to 3 periods of Treatment 1, participants learnt from the experiences of the previous rounds and there was indication that the data may converge to the EUE solution if more periods were considered. The UER solution provides the theoretical representation of Treatment 2, where participants are provided information. UER solutions are presented in terms of routing policy usage and as such the path flows need to be disaggregated for each state of the network. Comparing the observed state based mean path flow from the experiment to the theoretical solution indicates that the UER solution closely depicts the empirical behavior. The rounded integer values of each of the observed mean path flow values match exactly with the theoretical UER solution.

Table 2: Comparison of empirical and theoretical path utilization

Treatment 1: No Information					**Treatment 2: Information provided at Node C**				
	State	A-B-D	A-C-B-D	A-C-D		State	A-B-D	A-C-B-D	A-C-D
EUE Solution	E(S1,S2)	6	0	6	UER Solution	S1	4	0	8
Observed Mean Path Flow	S1	4.896	2.188	4.917		S2	4	5	3
	S2	5.130	1.688	5.182	Observed Mean Path Flow	S1	4.292	0.146	7.563
	Overall	5.083	1.788	5.129		S2	4.286	4.828	2.885

Table 3 displays a comparison of TSTC between treatments. The results of the experiment supports the presence of the Online Information Paradox, as the mean TSTC increases from 210.629 to 219.163 cost units when information is provided to the participants. However, the difference in mean TSTC between the two treatments is less than what was predicted in theory. The analytical solution suggests a difference of 24 cost units far greater than the 8.534 units observed on average during the experiment. This can be attributed to participants using *A-C-B-D* in the no information scenario resulting in a higher average travel cost for the system and straying away from the EUE solution. However, observing the latter periods of the data set, it is clear that the difference begins to reflect the theoretical predictions. The mean TSTC of the last 3 periods for the no information treatment is 194.833 units, while for the information treatment it is 219.333 units, again highlighting the initial periods of learning carried out by the participants. Another interesting observation is the difference in the standard deviation of the TSTC between the information scenarios. Intuitively, there is a far greater standard deviation in costs when no information is provided, as participants face greater rewards and losses associated with selecting route *A-C-B-D* and the uncertainty of the cost of link C-B. This contrasts the situation presented in Treatment 2, as individuals are able to adapt if State 1 of link C-B eventuates and there is an incident. The result suggests that though information has the potential to increase TSTC, there is a reduction in the variance of the travel costs observed within the system and as a result offers a greater degree of reliability.

Table 3: Comparison of travel costs between treatments

		Treatment 1: No Information		**Treatment 2: Information Provided at Node C**	
Period Analysis					
State		E(S1,S2)		S1	S2
Cost of A-B-D		16.871		14.438	19.115
Cost of A-C-B-D		18.588		32.146	17.828
Cost of A-C-D		16.917		17.708	17.714
Overall Mean TSTC		**210.629**		**219.163**	
σ_{TSTC}		24.948		15.470	
Theoretical TSTC		192		216	
Group Analysis					
Session Number	**Group Number**	**Mean TSTC**	σ_{TSTC}	**Mean TSTC**	σ_{TSTC}
1	**1**	212.200	26.411	220.300	13.739
1	**2**	209.650	25.887	218.600	12.701
2	**3**	209.800	19.259	215.800	11.181
2	**4**	210.550	21.333	220.600	14.233
3	**5**	217.500	36.699	215.900	10.228
3	**6**	212.600	34.014	229.150	26.650
4	**7**	213.850	35.445	216.400	14.591
4	**8**	208.750	16.676	215.800	15.477
5	**9**	204.700	15.815	220.800	17.025
5	**10**	211.850	20.254	217.600	13.068
6	**11**	205.350	16.925	219.100	13.082
6	**12**	210.750	22.583	219.900	16.613
Statistical Testing					
Period Analysis: Paired T-test (240 observations of TSTC)					
T-statistic		4.53811			
T-critical		1.96994			
p-value		0.00001			
Group Analysis: Wilcoxon Signed-rank Test (12 observations of mean TSTC)					
W-statistic		1			
W-critical		17			
p-value		0.000317			

In order to corroborate the observed empirical presence of the OIP, a paired T-test was completed to determine if the mean TSTC values were significantly different between the treatments. If the T-statistic exceeds the T-critical value there is a significant difference between the observed TSTC values. Table 3 clearly shows that when assessing the period data, the presence of the OIP is statistically significant. The period data used for the statistical analysis contained repeated measures of the mean TSTC for each group of participants across both treatments. For an example, group 1 contains 20 measures of mean TSTC, under each information regime. Thus, to account for repetition, a Wilcoxon Signed-rank test was used to compare the group mean TSTC statistics. The Wilcoxon Signed-rank test was used due to the small sample size relaxing the assumption of normality present in the paired T-test. To further emphasize the evidence, 11 out of the 12 groups (greater TSTC highlighted in orange within Table 3) within the experiment presented a statistically significant OIP at a confidence level of 95%. A Mann Whitney U-Test was also conducted using the group data to identify order effects. The group data was separated by treatment and the 6 observations of each order were compared, p-values exceeded 0.13, indicating no order effects and highlighting the consistency of the experimental procedure. These findings suggest that presence of the OIP is highly significant.

Participant learning questions the statistical analysis suggesting the empirical existence of the OIP, as data from all 20 periods of the experiment were analyzed collectively. It could be argued that the emergence of the paradox is an artefact of the data set. However, given that both Treatment 1 and Treatment 2 indicated that participants were learning and converging towards the analytical solutions, it is clear that upon learning, the manifestation of the OIP will most likely be stronger than what is presented within the aggregate analysis.

5 DISCUSSION AND LIMITATIONS

The results of the experiment indicate the empirical presence of the Online Information Paradox, where the provision of online information deteriorates the network performance and increases the travel costs for users. Furthermore, travel time variability reduces with the presence of information, consistent with the observations made by Lu et al. in 2012 and 2014 *(30, 31)*. This is evident as the standard deviation of TSTC in the information case across all assessments was considerably lower than that of the no information case.

It is also important to emphasize that online information provision, in general, will reduce travel costs and improve the efficiency of a network at an analytical and empirical level as presented in a number of studies *(30, 31, 37, 38)*. However, what is evident from this study and that by Rapoport et al in 2014 *(8)* is that for specific network topologies, there are situations where the provision of information can deteriorate network performance. Accordingly, based on the theoretical presentation of the UER framework and the corroborating empirical evidence, careful consideration of network structure is essential to avoid the emergence of such a paradox when evaluating the implementation of ATIS and ITS systems within road infrastructure.

The authors acknowledge that there are limitations within this study. The fundamental abstraction from reality is that travel cost was the only criteria used by participants in the route selection process. Route choice decisions are in general multi-objective where travelers consider travel time, reliability, tolls, road hierarchy and other factors *(39)*. The network and costs functions used to assess the paradox within the experiment are simplifications of reality. However, there is justification for this approach in an experimental as well as a cognitive context. In order to ensure control and reliability within an experiment, each participant must be able to comprehend the task to gain valuable insights *(24)*. In addition the simplification can be considered realistic as individuals cannot acquire as well as process all alternatives completely. Naturally, users reduce choice sets and simplify complex cost structures by evaluating the most important components *(40, 41)*.

6 CONCLUSION

The aim of this study was to investigate the empirical presence of a theoretical transportation paradox, defined as the "Online Information Paradox". The paradox suggests that the provision of online information deteriorated the travel conditions for individual users as well as the system as a whole. The analytical presence of the paradox was derived from two equilibrium models; the Expected User Equilibrium (EUE) solution explained the case where individuals did not have access to information while the User Equilibrium with Recourse (UER) solution depicted the case of online information dissemination at an intermediate node between origin and destination. Concepts of experimental economics were used to develop a controlled incentivized laboratory experiment consisting of a repeated computerized route choice game. The game emulated a 3 route stochastic network with an intermediate node that allowed a user to swap routes. The stochasticity of the network was dependent on the presence of an incident on a single link of the network with a given probability of occurrence.

Aggregate statistics of path flow and Total System Travel Cost (TSTC) were used to compare the empirical findings with the theoretical findings. A total of 12 groups of participants completed the experiment and the Online Information Paradox was observed in 11 of the 12 cases and its presence across all the data was statistically significant at a confidence level of 95%. Though the OIP was observed, the presence of information resulted in significantly lower standard deviations of system travel costs supporting the claim that information improves travel time reliability.

The observation of the Online Information Paradox in a controlled setting, as presented in this study, creates an additional consideration for transport authorities during the evaluation and implementation of ITS and ATIS infrastructure within a road infrastructure context. Replications of such experiments and more importantly field based identification of the phenomena will require transport professionals to be aware of the paradox. Finally, the study indicates that practitioners should consider adaptive traffic assignment techniques, such as UER, to appropriately model the acquisition of information on a road network.

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