THE DEVELOPMENT OF A FRAMEWORK TO MEASURE THE CONSISTENCY OF ONLINE USER EXPERIENCE

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ABSTRACT

This paper documents the development of a framework for measuring the consistency of online user experience on a large B2C site. The test case is a major airline that provides the sales of airfares and holiday packages via 12 different sites dedicated to different operating markets. To evaluate user-experience, the “Rubinoff’s User Experience audit” is modified to break online user experience evaluation into 4 elements; “branding”, “usability”, “functionality” and “content”. Web analytics are installed into the “branding” element only to suffice a thorough evidence-based analysis and to allow repeatability. The framework is then applied to different scenarios and results are analyzed to appraise the consistency of branding. The findings suggest that the B2C site exhibits poor consistency with respect to branding and direct implications in terms of user experience are discussed. This paper attempts to demonstrate how raw web analytic data maybe used to intelligently evaluate consistency via a proposed OUE framework. Recommendations for development of the OUE framework are also discussed.

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ABBREVIATIONS

UE	User Experience
OUE	Online User Experience
B2C	Business-to Consumer
RUEA	Rubinoff's User Experience Audit

CHAPTER 1: INTRODUCTION

1.1. CHAPTER OVERVIEW

This chapter provides a background to the study and accentuates upon the importance of the research being conducted. The purpose of study is described and a synthesis of the research problem is declared. From this, possible contributions and implications of the study are discussed.

1.1. Chapter Overview
1.2. Background to the Study
1.3. Importance of the Research
1.4. Purpose of the Study
1.5. Research Problem
1.6. Contributions and Possible Implications of the Study

1.2. BACKGROUND TO THE STUDY

Over the past decade, the World-Wide-Web has become the preferred vehicle for information dissemination on a global scale (Ferry & Blott, 2005). Similarly, the immense growth in electronic commerce has meant that contemporary B2C sites are now forced to cater for literally anyone and everyone. Today's large travel, auction, information and social networking sites are regularly visited by hordes of users that are as sociologically, demographically and geographically diverse as one can imagine, giving the notion of "online user experience" an entirely new meaning. Web production teams, perhaps over and above content on occasion, are now starting to prioritize "consistency" as a key feature that must be maintained during any website re-design, migration and/or integration. After all, as the majority of web users are often resistant to learning new procedures, consistency ensures sites remain undemanding to use and as a result, users derive maximum satisfaction from them. On the other hand, websites are constantly evolving, since contents requirements often change, the developing cycle is short, while the life cycle is long (Xu, Xu, Chen, & Chen, 2003). Given the obvious dilemma of consistency vs. evolving content, it is surprising that "consistency" in research dedicated to user experience design has been under-estimated. That is, little published work exists that dedicates itself to solely investigating 'consistency' as a component of 'Online Use Experience'.

1.2.1. What is consistency of OUE?

Currently, consistency in context of Online User Experience is a loosely defined concept. If ”consistency” is interpreted as keeping to a particular style or pattern, under the context of “online services” both “internal” and “external” consistency need to be appreciated (Gaffney, 2005). Internal consistency is concerned with application of established standards and conventions to throughout all the content on a particular website e.g. a user who is used to locating the “Search” box on the top right corner of a website will experience temporary problems if the box is arbitrarily shifted to different locations on other pages of the site. On the other hand, external consistency is concerned with correlation of a site’s usability against accepted general practice e.g. a user who is requested to enter credit cards details on an online site prior to selection of the product is likely to be both confused and annoyed. Studies into usability have concluded that web users tend to apply rules (Gaffney, 2005), conventions (Wiggins, 2006), etc that they have learned elsewhere and bring to every site their own experience and expectations despite the fact that these maybe inapplicable to their current site. Therefore, ignoring “external consistency” can cause confusion and alienation to potential visitors, and should be considered critical if a site is trying to attract new users or customers (Gaffney, 2005; Ozok & Salvendy, 2000, 2001). Ignoring “internal consistency” on the other hand can also cause confusion and sacrifice the online user experience of a website. If websites were static in terms of content, maintaining “consistency” would be effortless. However, to remain relevant, provide pertinent and up-to-date information, and promote events, services or activities, today’s websites are arbitrarily dynamic, data-driven and constantly evolving in terms online services they are able to offer. In evolving, they risk sacrificing consistency leading to the crux of the problem.

1.2.2. Motivations

The motivations behind this study are two-fold; ‘consistency’ measurement is a real-world problem for the practitioner in that no specific consistency measurement frameworks or tools exist. In retrospect, no existing research has investigated consistency in such detail that a practitioner can quickly invoke proven methods to holistically evaluate the consistency of online user experience on a given B2C site. Perhaps it is no surprise then that this study stems from the woes of managers at a major airline responsible for maintaining a large B2C site that enables customers to purchase airfares and holiday packages. The problem that they encounter is being unable measure or benchmark the consistency of online user experience on their B2C site, neither quickly nor accurately.

This is critical as their site is routinely subject to continuous development, integration and general change both in terms of content and online services. For example, in 2006 the airline launched a major off-spring site for a specific marketing initiative which is expected to remain in the future. As an on-going objective, the airline is attempting to reduce dependency upon vendor operated online booking engines and increase dependency on proprietary in-house engines which match routing & flight schedules and output bookings that are congruent with global distributions used by Reservations agents. In parallel, the main New Zealand (NZ) and Australian (AU) sites are subject to continuous improvement and extending service offerings beyond those associated with flight and holiday bookings, for example, allowing premium customers better maintain their airline membership profiles or allowing ordinary customers to perform auxiliary functions, such as seating requests, online check-in, etc. Citing a few examples only, quickly demonstrates possible causes that drive sites evolution. However, how is consistency ensured and assured? From the designer's perspective, the content management systems provide some guidelines in terms of site structure. Again, Styles guides and Cascaded Style Sheets (CSS) help streamline some content and presentation. Similarly, other website variables such as functionality and branding are loosely maintained. However, with different web production teams all attacking the same web space, the B2C site is subject to constant change. In short, while the airlines set of global sites are merely a test case for the purposes of this study; they can be beneficial for both justifying this study by bringing actual issues experienced by practioners to light. Key drivers and resistors have been identified in Fig. 1. Key "drivers" are those factors (or events) that are likely to drive website inconsistency. Key "resistors" are those tools that maybe be used to reduce the impact upon consistency and ensure web standards are maintained. What is apparent in Fig. 1 is that the tools available to maintain overall website consistency are both limited.

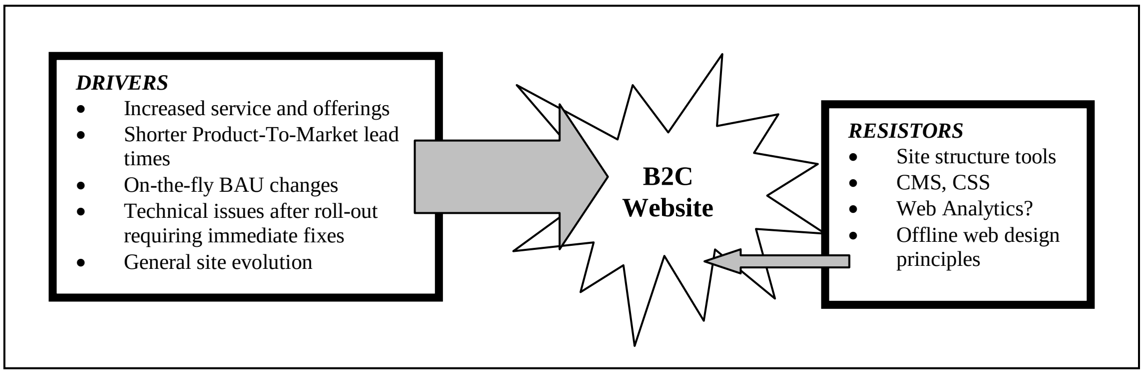

Figure 1 - Drivers/Resistors of consistency on large B2C sites

1.3. IMPORTANCE OF THE RESEARCH

This research has both implications for both commercial and academic work. A preliminary literature search has shown that consistency in online user experience is beginning to be understood but lacks formal analysis. However, consistency is cited as an important factor in helping strengthen the usability of any site and helping strengthen user-acceptance generally. Consistency in large B2C sites is especially important as these sites are responsible for converting prospective visitors into successful sales. Poor user-acceptance of a B2C has direct repercussions on revenue and to ensure maximum user-acceptance is the interest of the stakeholders. With the usage of the internet growing rapidly and a larger number of B2C sites being established on the web, increased competition is going to affect sales.

1.4. PURPOSE OF THE STUDY

The main purpose of this study is to develop a method to quantitatively measure the consistency of OUE and apply this to a given B2C site. For the purposes of this study, a case-study method is used as anomalies and short-comings are envisaged. Further, an ulterior purpose of this research is to document these anomalies and short-comings in order to allow future researchers to build upon on strategy for model development.

1.5. RESEARCH PROBLEM

The research problem is broadly composed of the following questions that will be examined via the two research objectives of this study – see 2.2.1 Research Objectives. It should be noted that the study has drawn upon OUE issues experienced by the test case B2C site and elected to test these using the OUE consistency framework developed. The OUE issues have been translated into different scenarios – this is discussed further in Section 3.5.3. Further, the study has been limited to testing a single OUE element "branding" for consistency.

(1) What constructs or frameworks are relevant to an assessment of online user experience on a large B2C site?

(2) What methods can be employed to assess consistency?

(3) How can the scoring technique be justified for both user experience and consistency measurements and how does this relate to existing ephemeral scales?

(4) What are the consistency measurements for each of the scenarios?

(5) What improvements can be diagnosed from the framework to improve the consistency of branding without adversely affecting online user experience?

1.6. CONTRIBUTIONS AND POSSIBLE IMPLICATIONS OF THE STUDY

The outcome of this study will be compromised of a deliverable that provides a suitable prototype framework for measuring consistency of online user experience. This dissertation documents the process of developing such a measure/construct/framework. Upon developing this framework, it will be used to offer recommendations towards improving consistency of online user experience using results from applying the framework to the test case. The framework will also contribute to existing body of work by proposing a novel framework and creating a platform for investigation of relationships between certain elements (or aspects) of “online-user experience”.

CHAPTER 2: LITERATURE REVIEW AND RESEARCH QUESTIONS

2.1. CHAPTER OVERVIEW

The purpose of this chapter is to review existing literature and conclude definitive research questions for the study. A definition of Online User Experience (OUE) is offered before formal methods used for evaluation OUE are reviewed and discussed. A discussion of consistency (as applied to OUE) follows, again via reviewing existing work done in the field. In conclusion, using gaps identified in the literature, the development of the research problem is documented where two research objectives (RO's) are identified spawning four individual research questions (RQ's).

2.1. Chapter Overview
2.2. Evaluating Online User Experience (OUE)
2.3. Measurement of Consistency
2.4. Development of the Research Problem

2.2. EVALUATING ONLINE USER EXPERIENCE (OUE)

As a relatively new area of investigation within the human-computer interaction (HCI) field, many researchers are only beginning to understand 'user experience' or even agree over a common definition. Some academics (Elaine, Christine, & Susan, 2004) like to place 'User Experience' adjacent to 'Functionality' and 'Usability' when discussing it within the context of designing and evaluating new technology, while others argue that 'User Experience' is indistinguishable from 'Usability' but instead merely its subset that chooses to focus on the user rather than on an isolated product attribute or a process (Christian & John, 2004). Some practitioners even encompass 'Usability' as an element of "User Experience". In short, what is apparent from the bulk of work is that there are no well-developed assessment methods or constructs available to measure 'user experience' and a case-by-case method is needed.

What has been discussed is no truer when discussing the state of research of 'user experience' in the context of websites, more popularly phrased as 'online user experience'. The bulk of work in this area is however divided philosophically; some profess that 'online user experience' can be completely measured using contemporary usability constructs, while others advocate broadening the usability construct to include more-subjective dimensions (Niamh & Jurek, 2006). A separate school of researchers advocate the need for novel constructs that are distinct from usability altogether (Schaik & Ling, 2007a). Yet another group, under the guise of "design reductionism" argues that user experience is independent of and cannot be deducted from product features (Banphot, Antonis, & Magid, 2004). The results achieved in mostly qualitative assessment of user experience make for excellent philosophical discussion but contribute little towards a universally accepted construct or framework. On the other hand, significant progress has been made in attempts to quantify online user experience via a variety of frameworks that rely on primarily on scoring and rating strategies (Elaine et al., 2004; Rubinoff, 2004). For example, to satisfy the needs for an objective analysis tool in measuring online user experience, a well-known practitioner Rubinoff has a developed a 'quick and dirty' audit methodology that assesses overall user experience by measuring four interdependent elements of a website; branding, usability, functionality and content. Each element is appraised by allocating a score (on a scale of 1 to 10) to a series of five statements (or parameters) against which the website in question will be measured. For example, one of the statements (or parameters) used to appraise 'Functionality' asks if 'Task progress is clearly communicated (e.g., success pages or email updates)'? Another, used to appraise 'Content' queries if 'Link density provides clarity and easy navigation?'. Overall, each element achieves a score out of a maximum of 50 and the results are displayed in a spider diagram. Repeat assessment using 'Rubinoff's User-Experience Audit' helps assess different sections of the site and if juxtaposed perhaps helps reveal the consistency of user experience? In a similar spirit, various academic papers have also attempted to 'measure' online user experience however via a far more sophisticated rating methodology. In attempting to measure user experience with digital libraries, researchers Elaine, Christine & Susan first validated then adapted the popular Experiential Value Scale (EVS) into an application-specific Digital Library User Experience Scale (DLues). These scales and similarly, the Rubinoff's User Experience are highly subjective are rely largely on questionnaires, user testing, etc. which introduces a large amount unreliability as associated with human testing.

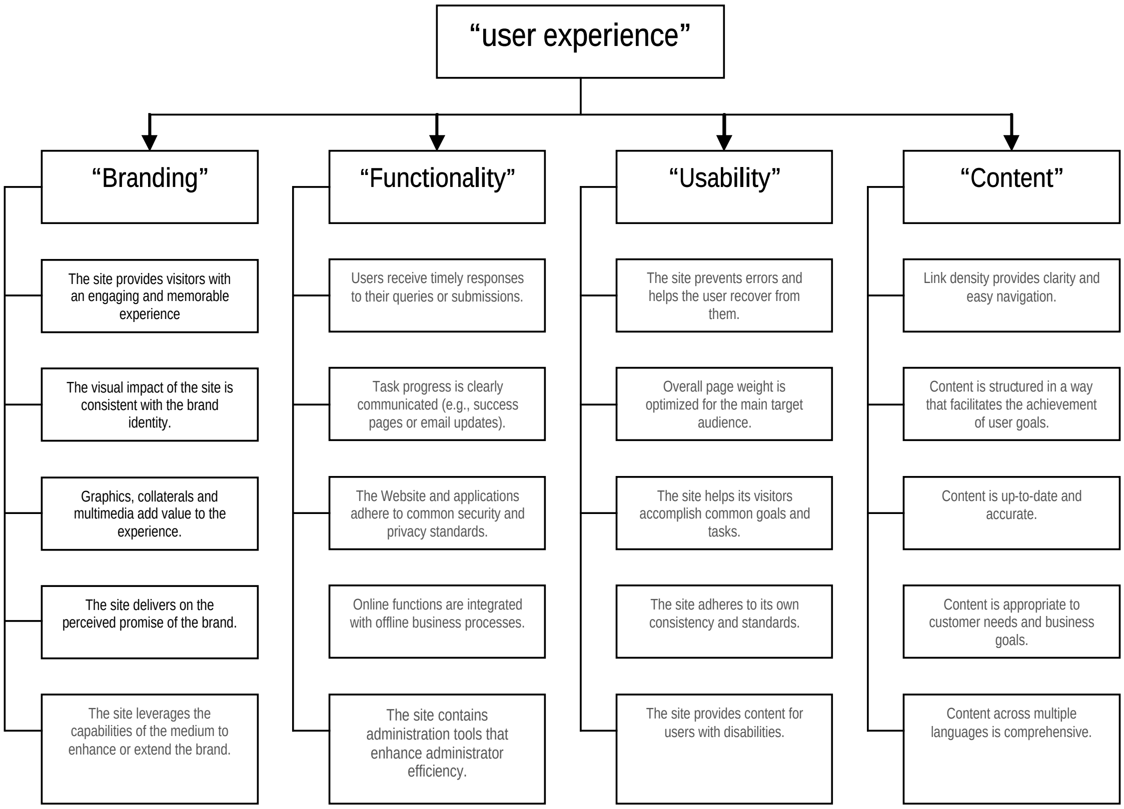

Figure 2 – Matrix adopted from Rubinoff’s User Experience Audit (Rubinoff, 2004)

2.2.1. Definition of OUE

Just as the literature searched returned a plethora of studies that revolved around evaluating the notion of user experience a variety of possible definitions have been discussed but never agreed upon. For the purposes of this study, a definition will be developed by considering the accepted and established notion of “user experience” and by applying this to the online realm. While the purpose of this study is not to argue upon definition, agreeing upon a definition will provide good focus when developing the framework.

2.2.2. Formal methods identified from literature

The purpose of this section is to summarize formal methods for assessing OUE that are popular in published academic work and by practitioners. Formal methods are recognized by this study as those that provide a clear algorithm, approach or method for calculating OUE as a whole or that of a website element that contributes to the overall OUE. To ensure there is focus, only a handful of publications from a sea of literature were selected. In selecting these publications, there has been an emphasis in demonstrating a diversity in (1) the formal methods used to study OUE (e.g. design parameters), (2) the context in which OUE has been studied (e.g. digital libraries, online advertising, etc.) and (3) the formal research method(s) that the published study has employed in order to collect data (experimental design, survey). The immediate point of significance that can be drawn from this table is that the website dimensions explored both by the practitioner's and academic's published papers resonate around functionality, usability, branding and content. Aptly these are also the website dimensions that feature in Rubinoff's User Experience Audit.

Table 1 – Summary of formal methods identified from literature for evaluating OUE

Author(s)	Research Method(s) used (if any)	Key focus of the published work/article	Website Dimensions Explored	Metric(s) used/identified (if any)
Wiggins, A. (2006).	None, exploratory research paper	Quantification of user experience by developing metrics for heuristics	Branding, Functionality, Usability, Content	Rubinoff User Experience Audit Matrix (RUEA)
(Notess, 2001)	None, exploratory research paper	Usability, user experience, and learner experience	Branding, Functionality, Usability, Content	None.
(Schaik & Ling, 2007b)	Experimental Design	Design Parameters of Rating Scales for Web Sites	Functionality, Usability	Ephemeral rating scales
(McNamara & Kirakowski, 2006)	None, exploratory research paper	Functionality, Usability, and User Experience Three Areas of Concern	Functionality, Usability	None
(Rubinoff, 2004)	None, practitioner	How To Quantify The User Experience	Branding, Functionality, Usability, Content	Rubinoff User Experience Audit Matrix (RUEA)

(Elaine et al., 2004)	Survey	Measuring the User's Experience with Digital Libraries Elaine G. Toms, Christine Dufour and Susan Hesemeier	Branding, Functionality, Usability, Content	None
(Rohrer & Boyd, 2004)	Case Study	The Rise of Intrusive Online Advertising and the Response of User Experience Research at Yahoo!	Branding, Functionality, Usability, Content	Three-legged Stool

2.3. MEASUREMENT OF CONSISTENCY

The importance of consistency in the context of (web) interface design problems has been emphasized by both by researchers (Ozok & Salvendy, 2000; Xu et al., 2003) and practitioners (Gaffney, 2005). Both groups agree that improved consistency makes a site generally easier to use, primarily because users are no longer forced to learn new protocol on how to navigate or complete tasks (Gaffney, 2005). Consistency as applied to website design has been explored in various contexts, again via both published work in academic journals and guides written by practitioners in the industry. Several empirical studies have even gone so far as to statistically prove that increasing consistency levels of interfaces results in significant reduction of error rates by users completing PC and web-based computer tasks (Ozok & Salvendy, 2000) while others have concentrated on processing server-side web analytic data for improvements in website structure, user efficiency, etc again using statistical analysis (Xu et al., 2003). However, while there is little doubt for the need for consistency, the majority of established frameworks used to measure consistency focus on specific attributes of a site as opposed to taking a holistic approach and studying for example, usability, functionality, user experience, etc. As it will be demonstrated, existing methods used to measure consistency are not only too specific but also incredibly draconian, employing robust statistical methods to confirm variance (or lack thereof). While this perhaps maybe necessary in proving a hypothesis in the context of academic work, it is arguable that "measuring the variance in font size" is too focused an analysis to offer any immediate practical significance to an organization or practitioner looking to measure consistency in a large B2C site on a regular basis, or post-site redesign.

2.3.1. Definition of "consistency" under the OUE context

The literature review reveals no work done where "consistency" as applied to OUE has been directly quoted or defined. To assist in offering a focus for this study, a definition of "consistency" under the context of Online User Experience has been self-developed as *"the degree to which the overall experience, in general or specifics, a {user, customer, or audience member} has with an online {product, service, or event} varies from one {occurrence, session or period} to the next"*. It is obvious that this definition requires needs further analysis and development; however this would be topic of future research work.

2.3.2. Formal metrics identified from literature

The study which aligns most closely to the research objectives investigated the effect of consistency on the performance and satisfaction of users (Ozok & Salvendy, 2000). In doing so the study demonstrated methods for measuring the consistency of various elements between group web pages. In particular, Ozok & Salvendy hypothesized that participants would perform better and be more satisfied using web pages that have consistent rather than inconsistent interface design; that the overall consistency level of an interface design would significantly correlate with the three elements of consistency, physical, communicational and conceptual consistency; and that physical and communicational consistencies would interact with each other (Ozok & Salvendy, 2000). Utilizing experimental design, participants were tested via a four-group, between-subject design, with 10 participants in each group. Each participant was firstly assigned with several different tasks that needed to be completed upon a series of webpages. The results partially supported the hypothesis regarding error rate, but not regarding satisfaction and performance time. However, the results supported the hypothesis that each of the three elements of consistency significantly contribute to the overall consistency of a web page, and that physical and communicational consistencies interact with each other, while conceptual consistency does not interact with them. In a later paper, Ozok & Salvendy developed a methodology to measure aspects of computer interface consistency and assess the impact of linguistic inconsistency of interface design on user performance using a survey approach. Seven factors were identified from background literature as affecting overall consistence, which was the basis for a structured questionnaire of 125 items. Using factor analysis the number of items in the questionnaire to 94 and the following nine factors were identified as contributing to consistency: text structure, general text features, information representation, lexical categories, meaning, user knowledge, text content, communicational attributes and physical attributes. The authors conducted four experiments were with 140 subjects using four different tasks and eight different interface types. They found their instrument effectively identified all of the inconsistencies in interface designs with internal reliability of 0.81, and the inter-rater reliability was 0.75.

The instrument can be utilized both as an evaluation and as a design tool for Web-based interfaces.

Researchers Ozok & Salvendy are not the only academic collaboration to complete notable quantitative studies in website analysis. In 2003, a group of researchers' (Xu et al., 2003) analyzed server side log files in a study focusing upon user responses and attitudes. Using visitor's information and server responses the researchers obtained a weighted structure model which was used to improve testing efficiency, improve the structure of the site, fulfill the functionality of the site, and enhance users' visiting efficiency.

The field has also invoked large quantitative studies to be completed. In 2005, Ivory & Megraw completed a longitudinal study of web site design from 2000 to 2003, analyzing over 150 quantitative measures of interface aspects that included the amount of text on pages, numbers and types of links, consistency, accessibility, etc. for 22,000 pages and over 1,500 sites that they claimed received ratings from Internet professionals. They examined characteristics of highly rated sites and provide three perspectives on the evolution of web site design patterns including descriptions of design patterns during each time period; the changes in design patterns across the three time periods; and also comparisons of design patterns to those that are recommended in the relevant literature e.g. user studies. In essence, they illustrated how design practices conformed to or deviate from recommended practices and the consequent implications. A founding conclusion was that the one of the most obvious deficiency of web sites, is their inadequate accessibility, in particular for browser scripts, tables, and form elements (Ivory & Megraw, 2005). This applied equally to sites that are highly rated.

Formals studies, albeit qualitative, that have focused on other aspects of a website such as its layout have also found that consistency is positively related to usability. For example, in a study by (Constantine & Lockwood, 1999), authors confirmed that keeping a consistent layout across pages enables ease of navigation when surfing through the pages. Several other studies confirm the importance of consistency in layout in web-design as it helps strengthen users' impression of the site (Scapin & Bastien, 1997) and reduces search time considerably (Tan, Tung, & Xu, 2009). Overall, consistent presentation (layout, organization, colour and navigation menu) throughout the whole website creates a deeper impression on users as they surf compared to inconsistent sites (Tan et al., 2009). In Tan, Tung, & Xu' study, participants in fact suggested ways to maintain consistency including the use of uniform organization, colors, font size and the way information is presented.

positioning of prominent features would reflect the main focus and purpose of the website, enabling users to recognize the website better.

Table 2 - Summary of formal methods identified from literature for measuring 'consistency'

Author(s)	Research Method(s) used (if any)	Key focus of the published work/article	Website Dimensions Explored	Metric(s) used/identified (if any)
(Ozok & Salvendy, 2001)	Experimental design	Interface consistency	Text structure, general text features, information representation, lexical categories of meaning, user knowledge.	Statistical ranking derived from custom ILCTQ and PCTQ questionnaires
(Ozok & Salvendy, 2000)	Experimental design	Measuring consistency of web page design and its effects on performance and satisfaction	text structure, general text features, information representation	Statistical ranking derived from custom ILCTQ and PCTQ questionnaires
(Ivory & Megraw, 2005)	Experimental design	Evolution of Web Site Design Patterns	Formatting of text elements, links and graphic elements, Page performance and site architecture, Color.	Custom metrics derived from statistical models
(Gaffney, 2005)	None, practioner	General consistency	Language, Layout, Function	None.
(Tan et al., 2009)	Repertory Grid Technique	Web-designers' Criteria for B2C Website Evaluation	Layout, Colors	None.

2.4. DEVELOPMENT OF THE RESEARCH PROBLEM

The gaps identified from the literature review provided a basis for developing the research problem and identifying research questions. While the problem of a lack of an OUE consistency measurement framework is truly apparent, it was necessary to identify if the research problem pertained to issues with existing OUE assessment methods because they don't encapsulate "consistency" or alternatively, if "consistency" was separate to OUE assessment altogether? The gaps identified that the latter was the case. Accordingly, one of the research objectives is to agree upon an OUE evaluation method, the results of which are subjected to consistency measurement.

2.4.1. Gaps identified from the Literature Review

The literature review demonstrated that there exist a number of popular evaluation methods used to evaluate OUE, however, none of these are aligned or even focus on similar OUE components. The disparity suggests two things –firstly, much development needs to happen with regards to OUE evaluation technique to an extent that a benchmark OUE evaluation method can be agreed upon. Secondly, measuring the consistency of OUE remains highly ambiguous in the field of web research. Therefore, in agreement with the preliminary literature review, a highly limited amount of published work exists that addresses the problem of inconsistency of OUE. Reverting to the original research problem, these findings can be recognized as significant gaps in knowledge in the area of OUE. However, not all of these gaps will be addressed by the study or form part of the research problem and accordingly, they have been omitted for discussion for the purposes of this study.

(1) **No agreed upon definition for "online user experience".** None of the published work offered a consistent definition of OUE nor consistently identified what components or traits OUE can be encapsulated by. Most authors aligned OUE as a subset of either 'usability' or 'user experience' in support of their research objectives.

(2) **No agreed upon (or offered) definition for "consistency" as applied to "online user experience"**. While consistency of different components of OUE (e.g. layout, font size, etc) was discussed, no appreciation for consistency of the total OUE was considered in any of the published work reviewed.

(3) **No rigorous framework or research methodology that measures "online user experience" was discovered.** Instead most OUE assessment methods were either exploratory or at best a survey of "user-experience" e.g. they could not be provide adequate repeatability without introducing significant bias – see **2.4.1**(6). Lack of repeatability is a significant problem as most practitioners would need to benchmark their B2C OUE to ascertain performance (or lack of performance).

(4) **Out of the limited number of OUE evaluation frameworks reviewed, no framework sought to quantitatively measure the consistency of OUE (or more than a single aspect OUE).** These findings suggest that web researchers have not officially bridged the gap between "OUE" and "consistency" – this is the major gap that exists and is the basis for the extended research problem and wider study.

(5) **No use of web analytic data to rigorously measure OUE.** While a variety of data sources (mainly derived from surveys and participatory testing) were used to evaluate web research, no evidence of use of web analytic data to measure OUE exists.

2.4.2. Research Questions

The overall research objectives (RO) are simple. Firstly, there is interest to engage in the development of a framework that allows us to measure the consistency of online user experience and secondly, testing the framework by applying it to a large B2C site. To provide some scope, for each of the research objectives some pertinent research questions (RQ) have been devised which in fact, changed during the process of completing the study – the implications of these have been left to the discussion section for analysis. The RQ's have been explored in Fig. 3 (below) and this follows with a brief explanation of the different scenarios that the framework will be used to test.

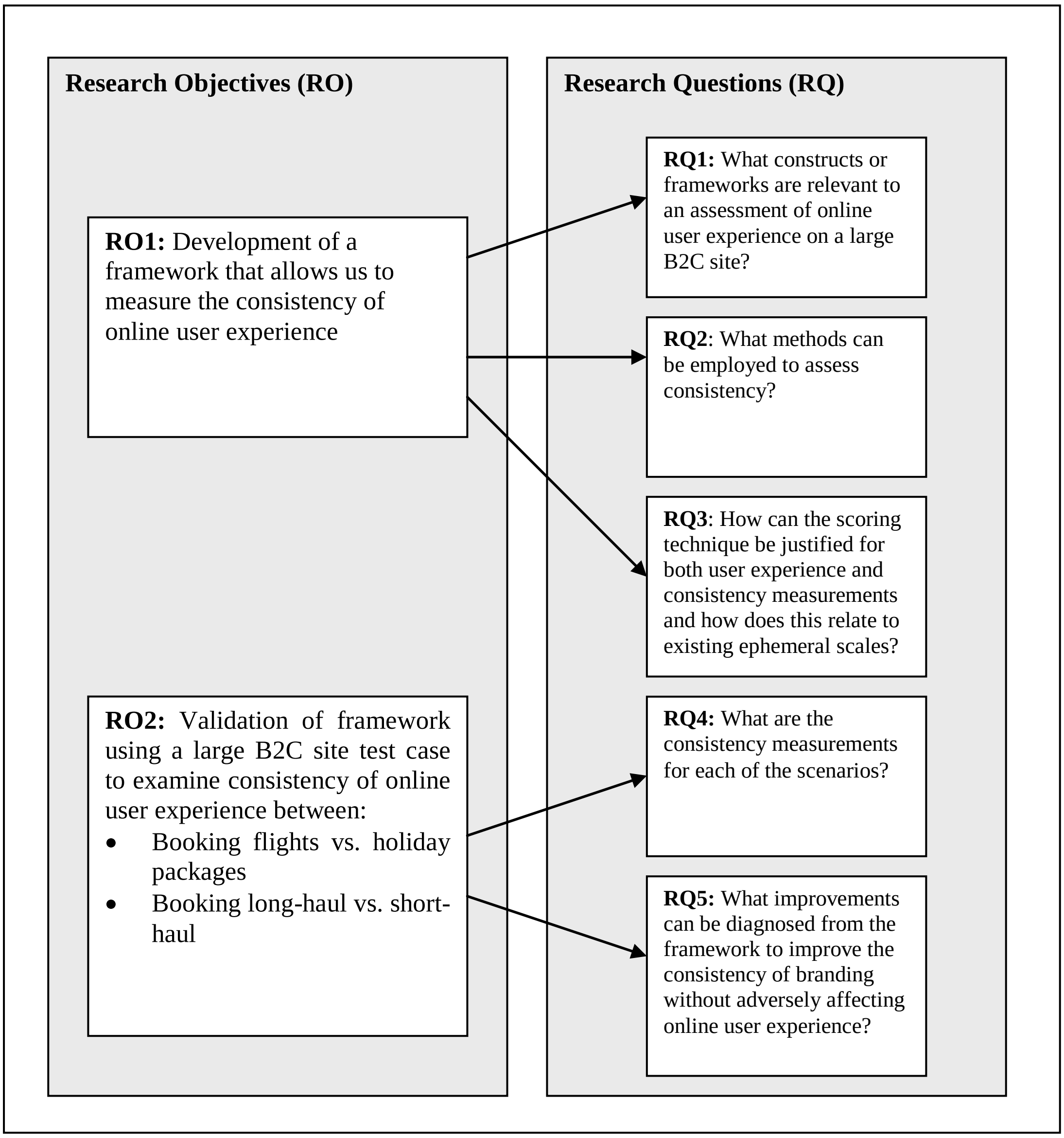

Figure 3 - Identifying research questions

CHAPTER 3: METHODOLOGY

3.1. CHAPTER OVERVIEW

This study formally employed an exploratory case study method to study 'online user experience' (OUE). Using a positivist epistemology, this paper also led the development of a novel framework to quantitatively evaluate the phenomenon and suggested a method to measure the consistency of branding. The proposed research methodology consists of five phases which are prescribed in the workflow below. In this section, the formal research approach taken is justified before a possible method of treatment for each of these of states is discussed which more carefully defines the proposed research strategy.

3.1. Chapter Overview
3.2. Justification of formal Research Methods
3.3. Development of A theoretical Framework
3.4. Methodology for Data Analysis
3.5. Application of the Framework to the Testcase B2C Site

3.2. JUSTIFICATION OF FORMAL RESEARCH METHODS

While the research objectives are generally well defined e.g. "to measure the consistency of online user experience" and the solution is to do just that by developing a framework and attempting to validate it via particular instance of a large B2C site, there still remains much ambiguity and speculation regarding the specific research operations that will be encountered and accordingly, the quality and applicability of the results. For example, while the proposed framework in this proposal has realized say, "branding, usability, functionality and content" as key elements of "online user experience" it cannot be ascertained that there are no other elements in the mix that would help evaluate user experience better and more importantly, what methods would be used to evaluate such elements? In response to this kind of uncertainty, it has been decided to concentrate the study on a single instance, e.g. a large B2C site of a major airline and adopt an exploratory case study as the overall research approach, however using a positivist epistemology in developing the framework. According to Yin 2002, a case study is an empirical inquiry that "investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident" (Yin, 2002). This study loosely conforms to such a description. That is, this study investigates "online user experience" via an empirical inquiry without knowing the exact boundaries this entails when applied to the large B2C site. In developing the quantitative framework, a positivist approach will be adopted primarily for two reasons. Firstly, to be able to validate the framework using statistical methods and secondly, to allow for repeatability – it is envisaged that the framework will be used repeatedly, given that consistency of typically any website is subject to change on a regular basis.

3.3. DEVELOPMENT OF A THEORETICAL FRAMEWORK

The development of a theoretical framework can be described in Fig. 1 below as a simple four step process.

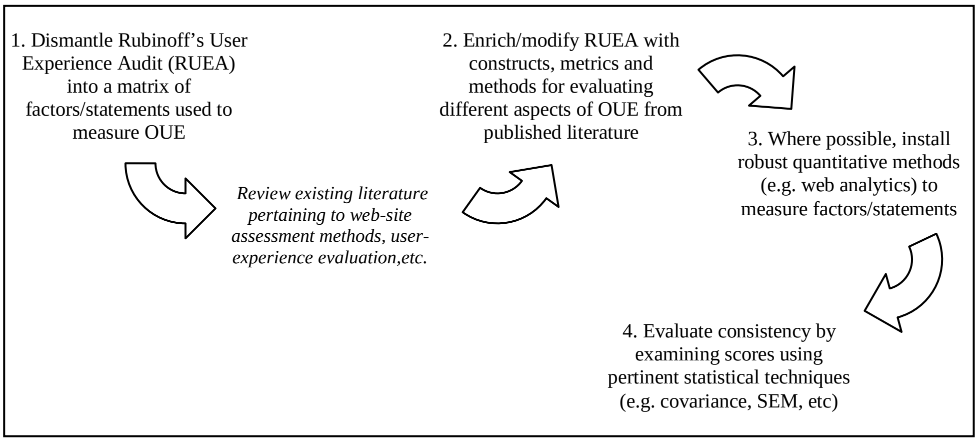

Figure 4 - Development of a theoretical framework for evaluating OUE

3.3.1. Strategy for OUE evaluation

Having reviewed a multitude of schemes to evaluate online user experience and appraised the merits and disadvantages of each in the preliminary literature review, it has been decided that a succinct two-step strategy to developing a novel theoretical framework.

1. Using Rubinoff's UE Audit as a starting point, where necessary, modify existing factors/statements used to assess each of the 'Usability' elements by replacing these with popular constructs from published work e.g. formal metrics identified from the literature review.
2. Review the newly developed UE audit matrix and where possible, install robust quantitative methods (e.g. web analytics) to measure factors/statements, while providing a suitable justification for doing so.

The overall objective will be to devise a scoring mechanism for each element of the user experience audit. The bulk of the work (under taken when developing the framework) will aim to justify and validate this particular scoring mechanism. While the ability to repeat research methods is paramount, the immediate motive behind keeping with a quantitative evaluation of the user experience is to aid in measuring its consistency with quantitative ease and allow an organization to utilize such a framework to help benchmark consistency.

3.3.1.1. Limiting the OUE evaluation for 'Branding' element

Given the formal expectation of the dissertation to a single semesters worth of study, the research has limited its scope to evaluating the 'Branding' RUEA element only. While all RUEA elements (e.g. "branding", "functionality", "usability" and "content") will be juxtaposed against relevant literature, part (1) and (2) of the strategy (as defined in 3.3.1) will be performed upon the five existing factors/statements attributed to "Branding" only. There is no particular reason why "Branding" has been selected except arbitrarily as the first element in RUEA matrix. Similarly, there is no evidence to suggest that "branding" has a greater or lesser contribution to the overall OUE. Further, this study does not investigate the weighting of different OUE elements and their contribution towards the overall OUE although this may be a topic for future research or discussion.

3.3.2. Comparing Rubinoff's UE Audit elements with relevant literature

The purpose of this section is to juxtapose the UE audit elements (prescribed in Rubinoff's Audit Matrix) against the relevant literature and if available, use metrics or tools currently used by practioners to addresses the different factors/statements. For the purposes of this dissertation, 'Relevant literature' is recognized as any formally documented study that has investigated website dimensions or has focused on themes that are prevalent with respect to the RUEA statements that fall under each RUEA element.

Rubinoff's UE Audit Element: Branding

According to (Rubinoff, 2004) "branding includes all the aesthetic and design-related items within a website". Applying this definition to the test case, 'branding' can be understood to entail anything from the airline logos to the colors exhibited on the website. For example, a website that uses colors strongly associated with a competitor would fail to "project the desired organizational image and message"(Rubinoff, 2004) and therefore may fare poorly under this element of the RUEA. Not surprisingly, the relevant literature most closely aligned to the factors/statements under "branding" repeatedly identified "content" as the website dimension – see Table 3. It must be noted that the literature review conducted did not reference any work that purely studied the phenomenon of "brand experience" as this work was found to give limited (if any) focus to "branding" in the online realm. Again, there is no doubt that "offline" and "online" branding for an organization aren't inextricably linked but this study places a focus on OUE and not "branding". What was encouraging to find was that different factors/statements in the RUEA addressed different themes as reflected by relevant literature. This provided some assurance that the RUEA (a practioner's perspective of OUE) did assess the "branding" element of a website holistically.

Table 3 - Comparing Rubinoff's UE Audit element 'Branding' with relevant literature

Existing factor/statement from RUEA	**Relevant literature**			**Metrics/Tools currently used by practitioners (if any)**
	Author(s)	Common Themes	Applicable Website Dimensions	
"The site provides visitors with an engaging and memorable experience"	(S. F. Abdinnour-Helm, Chaparro, & Farmer, 2005), (Agarwal & Venkatesh, 2002)	Satisfaction, Usability	Content	Ratio of returning visitors over time
"The visual impact of the site is consistent with the brand identity"	(Tan et al., 2009), (Agarwal & Venkatesh, 2002), (Subramaniam, Shaw, & Gardner, 2000), (Reed & Groth, 2008)	Brand identity	Content	Conformance to Style guides
"Graphics, collaterals and multimedia add value to the experience"	(Reed & Groth, 2008), (Perfetti & Landesman, 2001), (Tan et al., 2009), (J W Palmer & D A Griffith, 1998)	Graphics, Multimedia, Site Performance	Content	Web Analytic tools specific to, multimedia technology etc.
"The site delivers on the perceived promise of the brand"	(Banphot et al., 2004), (Evans & King, 1999)	Brand	Numerous	User Surveys
"The site leverages the capabilities of the medium to enhance or extend the brand"	(Evans & King, 1999), (Banphot et al., 2004), (McKinney, Yoon, & Zahedi, 2002)	Brsnd	Numerous	User Surveys

Rubinoff's UE Audit Element: Functionality

According to (Rubinoff, 2004) functionality "includes all the technical and 'behind the scenes' processes and applications". Rubinoff furthers this definition by encapsulating "site's delivery of interactive services to all end users including administrators". Therefore in locating relevant literature, the focus has been on research that has investigated website performance and the development (or use of) metrics for measuring this performance. As demonstrated in Table 4, the common website dimension explored by all papers is 'performance' as applied to their respective contexts, e.g. query results. There was poor alignment of literature against the RUEA factors/statements for 'functionality' as compared to other RUEA elements, with no closely matching literature being found for the final statement pertaining to administrator efficiency. While RUEA statements for 'functionality' offer pragmatic methods to measure performance (e.g. receipt of timely response to queries) closely aligned literature offers complex & theoretical models.

Table 4 - Comparing Rubinoff's UE Audit element 'Functionality' with relevant literature

Existing factor/statement from RUEA	**Relevant literature**			**Metrics/Tools currently used by practitioners (if any)**
	Author(s)	Common Themes	Applicable Website Dimensions	
"Users receive timely responses to their queries or submissions"	(Pandey, Ramamritham, & Chakrabarti, 2003)	Performance metrics	Currency of query results	Various Continuous Adaptive Monitoring (CAM) tools
"Task progress is clearly communicated (e.g., success pages or email updates)"	(McNamara & Kirakowski, 2006), (Venkatesh & Ramesh, 2006)	Tasks	Performance, Reliability and Durability	Content Management System tools
The website and applications adhere to common security and privacy standards.	(Miyazaki & Fernandez, 2000),	Security, Privacy, Disclosure	Compliance	External IS audits, W3C guidelines
"Online functions are integrated with offline business processes"	(McNamara & Kirakowski, 2006), (McKinney et al., 2002)	Goals, tasks	Performance, Reliability and Durability.	Manual Observation & Business Analysis
"The site contains administration tools that enhance administrator efficiency"	No relevant academic literature found.	-	-	No existing tools – site administrators typically review white papers and documentation to understand administrator tools.

Rubinoff's UE Audit Element: Usability

According to (McNamara & Kirakowski, 2006) usability can be regarded "as characteristic of the interaction between the user and the product". Rubinoff's usability statements echo this regard but issue specific factors/statements that enable a practitioner to measure specific elements of usability. The literature review returned a diversity of papers pertaining to each RUEA usability factor/statement. However, there was considerable difficulty in aligning literature to RUEA statements. While the RUEA focuses on specific dimensions, the literature sampled studied/discussed a common theme (under the topic of "usability") and then attempted to apply this to a range of dimensions. This applied to all papers except (Perfetti & Landesman, 2001) who offered a rudimentary analysis of how page weight can affect "ease of access" but with little insight to the methodology used to measure page weight and no agreed definition of "ease of access".

Table 5 - Comparing Rubinoff's UE Audit element 'Usability' with relevant literature

Existing factor/statement from RUEA	**Relevant literature**			**Metrics/Tools currently used by practitioners (if any)**
	Author(s)	Common Themes	Applicable Website Dimensions	
"The site prevents errors and helps the user recover from them"	(S. F. Abdinnour-Helm et al., 2005), (Agarwal & Venkatesh, 2002)	Ease of use	Numerous	the percentage of site visits including a 404 (file not found) error
"Overall page weight is optimized for the main target audience"	(Perfetti & Landesman, 2001)	Ease of access	Page weighting	Browser & Connection speed checks embedded within the page code
"The site helps its visitors accomplish common goals and tasks"	(McKinney et al., 2002), (Schaik & Ling, 2007b), (Elaine et al., 2004)	Tasks, Online processes	Tasks	the percentage of visits ending with other errors.
"The site adheres to its own consistency and standards"	(Tan et al., 2009), (Ozok & Salvendy, 2000), (Ferry & Blott, 2005; Ozok & Salvendy, 2001)	Website consistency, interface consistency	Numerous	the percentage encountering a 500 (server) error
"The site provides content for users with disabilities"	No relevant academic literature found.	-	-	Detailed design guide, Section 508 compliance

Rubinoff's UE Audit Element: Content

According to (Huizingh 2000) a key characteristic behind a B2C website is its content. So much so, that content can be a key factor in influencing a consumer's purchase decision while the design helps to attract and retain his interest at a site (Ranganathan et al. 2002). Accordingly, the literature review returned a plethora of studies that looked at a variety of website dimensions that affected website content – see Table 6. However, as Rubinoff's factors/statements for "content" focus on user/business goals and align with literature poorly. For this reason, no specific metrics/tools could be absorbed from the literature. This with exception to Waite who performed a study of a bank website and offered some guidelines to assessing the "appropriateness" of content with respect to business and user goals.

Table 6 - Comparing Rubinoff's UE Audit element 'Content' with relevant literature

Existing factor/statement from RUEA	**Relevant literature**			**Metrics/Tools currently used by practitioners (if any)**
	Author(s)	Common Themes	Applicable Website Dimensions	
Link density provides clarity and easy navigation.	(J. W. Palmer & D. A. Griffith, 1998)	Matching Site Design with Information Intensity	Site structure	Link Density Analysis
Content is structured in a way that facilitates the achievement of user goals.	(Agarwal & Venkatesh, 2002)	Usability	Usability	Link Density Analysis
Content is up-to-date and accurate.	(Griffiths, 2001)	Quality of web based information on treatment of depression: cross sectional	Content quality, content accuracy	Page Expiry, Visual Checks, Proofing
Content is appropriate to customer needs and business goals.	Waite	Consumer expectation of online information provided by bank Web sites	Goals and tasks	Manual review against a content guide, user experience survey
Content across multiple languages is comprehensive	Shihong Huang Scott Tilley	Content and Structure for a Multilingual Web Site	Design, Documentation, Human Factors, Standardization	Manual review against a content guide, user experience survey

3.3.3. Modifications to Rubinoff's OUE Audit Matrix

The purpose of this section is to, where possible and justified, categorically replace existing scoring mechanisms with measurements that can be derived from web analytics.

Rubinoff's UE Audit Element: Branding

Measuring "brand value" is a highly subjective art and a substantial amount of research (typically in the field of marketing) has already been performed, the results of which are constructs and mechanisms that facilitate its measurement. Accordingly, evaluating Rubinoff's UE Audit Element "Branding" using web analytics can be criticized as frivolous treatment of a UE element. That said, some researchers (Banphot et al., 2004; Rohrer & Boyd, 2004; Wiggins, 2006) will agree that as "direct measurement of brand is elusive in any medium" the use of web analytics' would facilitate gathering of tangible evidence (even if indirectly sought) than other brand evaluation techniques does using most other channels.

1. "The site provides visitors with an engaging and memorable experience"

There is evidence to suggest that a previous "engaging" and "memorable" online experience, will result, on average, in a visitor returning to the website (or online application) (McMillan, Hwang, & Lee, 2003). This would suggest that the ratio of returning visitors constitutes a valid metric to gauge the ephemeral value of a brand in this context. However, it should be noted that the return visitor ratio depends on the nature and theme of a site i.e. technical support sites would ideally prefer a smaller percentage of return visitors, however for the purpose, a large B2C ecommerce site would find returning users as positive. Therefore, as suggested by (Wiggins, 2006) measuring any OUE Audit Element such as "Branding" would require establishing a KPI tracked over time, i.e. an expected proportion of return visitors for the site which would need to be empirically established. It can therefore be ascertained that the frequency with which visitors return to a site indicates that the site is providing visitors with an engaging and memorable experience.

2. "The visual impact of the site is consistent with the brand identity"

Quantifying the "visual impact" of any site is difficult without direct user feedback. To understand the visual impact factor, studies that have been designed to measure the perceptions of the visual design of websites maybe cited. (Reed & Groth, 2008) studied approximately 400 different political websites and collated a set of heuristics that suggested leading to more favorably perceived website designs based on visual design. A number heuristics correlated visual impact positively with how extensively a visitor interacted with a given website. That is, a site with a “greater” visual impact would, on average, result in a higher level of interactivity by the user with a site.

3. “Graphics, collaterals and multimedia add value to the experience”

“Engaging online experiences like multimedia games, Flash, and AJAX are all measurable, but only if the design incorporates JavaScript tagging to report key interactions. Developing a measurement for multimedia after the site planning phase is not easy” (Wiggins, 2006). Rudimentary measures e.g. pages loading too slowly enable researchers to the measure the experiential value of graphics, collaterals and multimedia. Clickable graphics & interactive elements leading the user to further content do provide further empirical evidence of user activity. It is suffice that, for a site with a high frequency of return visitors, indicate that users interact with a given website more extensively and therefore are likely to spend more time on the site (Banphot et al., 2004).

4. “The site delivers on the perceived promise of the brand”

While it maybe argued that “the length of the average site visit, in both time and pages viewed provides verification of the brand experience” (Wiggins, 2006), a better measure might be to observe ‘visitor loyalty’. Loyal visitors are those visitors that are likely to be highly engaged with the brand and therefore likely to result in a high number of multiple visits. This would indicate good customer/visitor retention or “loyalty”.

5. “The site leverages the capabilities of the medium to enhance or extend the brand”

It is reasonable to argue that a site that leverages the capabilities of the (internet) medium is likely to experience a higher level of interactivity, provided that that capabilities that are being leveraged are indeed relevant to its visitors (Banphot et al., 2004; González & Palacios, 2004). For example, a travel website that offers both international and domestic bookings along with electronic ticketing is likely to experience higher levels of interactivity than a site that only offers a static sheet of travel schedules. If its is accepted that a site that experiences a larger number of high page views per visit is hosting visitors that interact more extensively with the site, this factor/statement maybe adjoined with a quantitative web analytic metric.

Table 7 - Summary of modifications to Rubinoff's OUE Audit Matrix for 'Branding'

Rubinoff's UE Audit Element: Branding			
Existing factor/statement from RUEA	**Modification**		**Justification**
	Modified factor/statement based on the RUEA	Nature of Metric/Dimensions	
"The site provides visitors with an engaging and memorable experience"	"The frequency with which visitors return to your site indicates the site provides visitors with an engaging and memorable experience"	*Number of visitors returning over a specified period*	A previous "engaging" and "memorable" online experience, will result, on average, in the visitor returning to the website.
"The visual impact of the site is consistent with the brand identity"	"The number of single page visits on the site indicates how in-extensively visitors interact with your brand"	*Number of single-page views visits vs. number of visits when more than a single page is viewed.*	A site with a "greater" visual impact would, on average, result in a higher level of interactivity by the user with a site.
"Graphics, collaterals and multimedia add value to the experience"	"The amount of time visitors spend interact more extensively with your site indicate graphics, collaterals and multimedia add value to the experience"	*Length of visits*	A high frequency of return visitors would indicate that users interact with a given website more extensively and therefore are likely to spend more time on the site.
"The site delivers on the perceived promise of the brand"	"The number of multiple visits and new visitors indicates the site delivers on the perceived promise of the brand"	*Number of multiple visits*	Loyal visitors are likely to be frequently and highly engaged with the brand e.g. likely to result in a high number of multiple visits.
"The site leverages the capabilities of the medium to enhance or extend the brand"	"The level of site interactivity on each visit acknowledges the level at which the site leverages the capabilities of the medium to enhance or extend the brand"	*Number of high page views per visit*	Experiencing a larger number of high page views per visit is hosting visitors that interact more extensively with the site.

3.3.4. Modified OUE Audit Matrix

To finalize the modified OUE audit matrix web analytic measures to OUE Audit elements are mapped.

3.3.5. Mapping web analytic measures to OUE Audit elements

Table 8 - Mapping web analytic measures to OUE Audit element 'Branding'

Rubinoff's UE Audit Element: Branding				
Rubinoff's OUE Audit	**Modified OUE Audit**	**Web Analytic Measure**		**Provider**
		Measure(s)	Comments	
"The site provides visitors with an engaging and memorable experience"	"The frequency with which visitors return to your site indicates the site provides visitors with an engaging and memorable experience"	*Visitor Recency*	• The frequency with which visitors return to your site can indicate their level of engagement with your brand and their readiness to buy. • Visitors are categorized according to the number of days that have elapsed since their last visit. e.g. example, new visitors are included in the "0" bar at the left of the histogram.	Google Analytics
"The visual impact of the site is consistent with the brand identity"	"The number of single page visits on your site indicates how extensively visitors interact with your brand"	*Bounce Rate*	• Bounce rate is the percentage of single-page visits (i.e. visits in which the person left your site from the entrance page). • Bounce rate is a measure of visit quality and a high bounce rate generally indicates that site entrance (landing) pages aren't relevant to your visitors.	Google Analytics
"Graphics, collaterals and multimedia add value to the experience"	"The amount of time visitors spend interact more extensively with your site indicate graphics, collaterals and multimedia add value to the experience"	*Length of Visit (Visitor Behavior)*	• Length of visit is a measure of visit quality. • A large number of lengthy visits suggest that visitors interact more extensively with your site. • The graph allows you to visualize the entire distribution of visits instead of simply the 'Average Time on Site' across all visits. • Keep in mind that 'Average Time on Site' is skewed by visitors leaving browser windows open when they are not actually viewing or using your site.	Google Analytics
"The site delivers on the perceived promise of the brand"	"The number of multiple visits and new visitors indicates the site delivers on the perceived promise of the brand"	*Loyalty (Visitor Behavior)*	• Loyal visitors are frequently highly engaged with your brand and a high number of multiple visits indicate good customer/visitor retention. • A high number of new visitors (i.e. those on the left of the histogram) indicate strong visitor recruitment. On th_s histogram, your most loyal visitors are shown on the right and your new and least loyal visitors are shown on the left.	Google Analytics
"The site leverages the capabilities of the medium to enhance or extend the brand"	"The number of visits with high page views acknowledges that the site leverages the capabilities of the medium to enhance or extend the brand"	*Depth of Visit (Visitor Behavior)*	• Depth of visit is a measure of visit quality. • A large number of high page views per visit suggests that visitors interact extensively with your site.	Google Analytics

3.4. METHODOLOGY FOR DATA ANALYSIS

Given that the user experience has been able to be quantified and set of normalized scores outputted for each element of the newly constructed matrix, the process of measuring consistency will be relatively easy task. Correlation techniques can be readily applied to compare overall scores for each element and also compute a covariance matrix to evaluate consistency overall. To compare how different factors contribute to each element, in possible future work, Confirmatory Factor Analysis could be utilized and this may provide understanding over the ranking of user experience elements in terms of maintaining consistency and also the nature of the linkages between them.

3.4.1. Examining consistency using correlation techniques

Correlation is typically applied to measure the strength and direction of a linear relationship between two variables. In this study, there exists a host of variables representing 'Evaluative Points' under each User Experience element. Evaluative Points are simply the measures used to evaluate a particular user experience element, e.g. Branding. For example, one 'Evaluative Point' under User Experience element "Branding" considers whether "The site provides visitors with an engaging and memorable experience". To keep things simple, an arbitrary number of 5 'Evaluative Points' has been selected for each of the 5 User Experience Elements. Therefore, if the matrix is used in its original form 5 elements by 5 evaluative points will augment 25 variables for each webpage analyzed. As mentioned in the previous section, prior to submitting this data for consistency analysis, each of each these variables would be normalized to give us a score[1].

In the first stage of analysis, only the following processed scores will be sought:

- Normalized total user experience scores for the 'branding' element only.

Correlation techniques will then be used to examine each of the following measures:

- Covariance between normalized total user experience scores for each scenario (consisting of a collection of pages), e.g. booking flights, booking packages, etc.

Interpreting covariance data in terms of assessing consistency

The total user experience score will represent the addition of all individual user experience scores from the matrix. The scores will be based on the new metrics that have been installed and normalized to ensure no one element ranks higher unless otherwise intended. In terms of measuring consistency these scores per page are useless and inform the researcher little. However, comparing these scores to other pages is useful and incidentally the basis for calculating the covariance. Covariance between two datasets (a, b) is typically defined as the tendency to vary together. In this study, the covariance between different 'Evaluative Points', 'User Experience' Scores, etc. will be calculated. The resulting (ca,b) value will be larger than 0 if a and b tend to increase together, below 0 if they tend to decrease together, and 0 if they are independent. Summarizing, individual user experience scores for each PAGE will not be interpreted individually, e.g. for pages such as the splash page (including the fast fare finder), etc. instead the measures and their means of interpretation as shown in Fig. 3 is suggested.

3.5. APPLICATION OF THE FRAMEWORK TO THE TESTCASE B2C SITE

Developing a framework is a completely adjacent process to applying it to a particular site, be it a test case or in practice. It should be noted that simply collating web analytic data and processing this against some rudimentary statistical method will generate no new knowledge. Remembering that an exploratory study has been undertaken, the freedom exists to to test the framework by attempting to resolve existing OUE issues. That is, the background and structure of the test case site are understood andthe OUE issues at stake are understood, before the framework is applied. This approach will help drive the way to process and present the raw web analytic data.

3.5.1. Test Case B2B background

The background of the test case B2C site has been more fully mentioned in Section 1 but important points have been listed here.

(1) The test case B2C site belongs to a major airline and is used to provide the sales of airfares and holiday packages via 12 different subsidiary sites dedicated to different operating markets.

(2) Currently, web production managers are unable measure or benchmark the consistency of online user experience on their B2C site, neither quickly nor accurately.

(3) In 2006, the airline launched a major off-spring site for a specific marketing initiative which is expected to remain in the future.

(4) The airline will continue to launch smaller off-spring sites again, for specific marketing initiatives.

(5) The main New Zealand (NZ) and Australian (AU) sites are subject to continuous improvement and extending service offerings beyond those associated with flight and holiday bookings, for example, allowing premium customers to more easily maintain their airline membership profiles or allowing ordinary customers to perform auxiliary service functions, such as seating requests, online check-in, etc.

However, given the formal limitations on this study, the New Zealand (NZ) site has been focused upon.

3.5.2. Test Case B2C Website Structure

The test case B2C website has the following structure at the time of this study – see Fig. 6

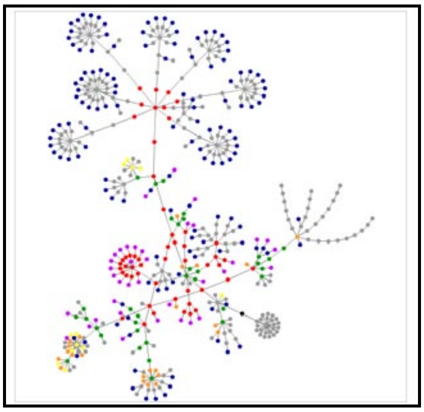

Figure 5 - Test Case B2C Website Structure[2]

3.5.3. Existing OUE issues with the Test Case B2C website

The following issues exist which are essentially comprised of different scenarios.

Booking flights vs. holiday packages

Currently booking flights and holiday packages involve different processes for the user. Flights being point to point air-travel and holiday packages encompassing flights together with land-only items such as hotel accommodation, car rentals, etc. At any rate, the different 'workflow' a user experiences to achieve either completing a flight or holiday booking is significantly different and can be detrimental to a sale of either or result in need

[2] Image created using 'Webpages as Graphs' online tool http://www.aharef.info/static/htmlgraph/

for extended technical support. Typically, travelers have experienced booking flights and intend to apply to the vaguely similar protocol to booking a holiday.

Booking "Long-Haul" vs. "Short-Haul" flights

Long-haul flights as defined by the airline are flights beyond Australia and Tasman-Pacific belt while short-haul flights are flights within this belt and include domestic flights within New Zealand. Again, somewhat due to the nature of travel, booking these types of flights involve a different "online user experience" primarily due to the way the website content (e.g. availability vs. fares) are displayed and other miscellaneous content items (e.g. the inclusion of taxes and need for passport details). Essentially, if the user is choosing to complete a multi-stop short-haul booking the workflow he/she experiences is different as compared to a long-haul booking.

3.5.4. Specification of the sample of web analytic data

Before web analytic data is hastily extracted, some thought needs to be given to the sample data. Firstly, web traffic is arbitrarily dynamic in nature and by taking a sample from a specific period it would automatically absorb a large amount of bias in the study, e.g. bookings for holiday's packages maybe higher than normal on weekends or domestic flights maybe more often booked during the work week. To minimize this bias, all the web analytic data extracted was an average from three equal periods over a span of 1 year In particular, sample data was acquired from 1st July 2007 to 30th June 2008. These dates were selected in particular as it was verified that the site structure and online processes (that users were exposed to) were identical. Secondly, there are some limitations to the web analytic tool used by the airline – Google Analytics only tracks pages that contain the Google Analytics tracking code. These can be considered as 'probes'. For this test case B2C site, only 500 probes exist, some of which point at specific pages, some of which point at specific Java functions.

CHAPTER 4: DATA ANALYSIS

4.1. CHAPTER OVERVIEW

In the previous chapter, web analytic measures were mapped against various factors/statements that belonged to different OUE elements. In this chapter, for the OUE element 'branding' only, raw analytic data from Google Analytics is extracted as per the schema, the processed data is then indexed to give normalized scores and finally consistency of OUE is determined by correlating the scores under different user-experience scenarios. This chapter is essentially a pilot test of the framework and demonstrates how raw web analytic data maybe be used to make intelligent conclusions regarding consistency.

4.1. Chapter Overview
4.2. Extracting web analytic data for OUE evaluation
4.3. Measurement of Consistency

4.2. EXTRACTING WEB ANALYTIC DATA FOR OUE EVALUATION

Extraction of all web analytic data consisted of applying probes to specific web pages and extracting raw data in terms of visits. To ensure consistency in the approach taken, data collection and collation was scoped to the different OUE scenarios that were required to be investigated e.g.

- Booking Flights Only
- Booking Holidays Only
- Booking Short-Haul flights
- Booking Long-Haul flights

Given this as a basis, all webpage's that a typical user may encounter under a given scenario were identified and probed. Data was collated in raw format e.g. number of visits against different metrics as per Google Analytics.

4.2.1. Web Analytic Results for 'Visitor Recency'

'Visitor Recency' can be defined as "the frequency with which visitors return to a given site" and this suggests "their level of engagement with the brand and their readiness to buy" i.e. visitors who are heavily engaged with a particular brand are likely to revisit the brands website more often. By default, "visitors are categorized[3] according to the number

[3] For example, new visitors are included in the "0 days ago" while visitors who last visited the site more than one year ago are included in the 366+ bar.

of days that have elapsed since their last visit". Table 9 demonstrates some interesting findings. Firstly, for all scenarios more than half of the total visitors have never previously visited the website, e.g. from the perspective of the airline these maybe new customers. Secondly, that just over a tenth of total visitors visited website 1 day ago and have returned. Also, each day thereafter accounts for anywhere between 1-6% of all total visitors each. Most importantly however, it should be noted that these 'Visitor Recency' scores are generally consistent across different scenarios suggesting visitors do not discriminate their level of engagement based on the type of travel product offered. That is, raw data suggests the test case website demonstrates strong consistency with respect to level of engagement with the brand.

Table 9 - Summary of Web Analytic Results for 'Visitor Recency'

Last Visit	Booking Flights Only		Booking Holidays Only		Booking Short-Haul		Booking Long-Haul	
	Visits	Percentage of all visitors	Visits	Percentage of all visitors	Visits	Percentage of all visitors	Visits	Percentage of all visitors
0 days ago	3,813,523	60.41%	823,044	59.96%	2,626,174	62.71%	1,187,349	55.88%
1 days ago	689,950	10.93%	154,416	11.25%	437,476	10.45%	252,474	11.88%
2 days ago	312,667	4.95%	62,733	4.57%	219,995	5.25%	92,672	4.36%
3 days ago	216,668	3.43%	47,871	3.49%	158,647	3.79%	58,021	2.73%
4 days ago	146,973	2.33%	35,421	2.58%	84,420	2.02%	62,553	2.94%
5 days ago	114,744	1.82%	27,407	2.00%	57,718	1.38%	57,026	2.68%
6 days ago	97,820	1.55%	22,297	1.62%	53,356	1.27%	44,464	2.09%
7 days ago	75,040	1.19%	17,012	1.24%	51,910	1.24%	23,130	1.09%
8-14 days ago	270,544	4.29%	57,283	4.17%	154,652	3.69%	115,892	5.45%
15-30 days ago	218,752	3.47%	46,143	3.36%	113,661	2.71%	105,091	4.95%
31-60 days ago	142,760	2.26%	29,822	2.17%	90,099	2.15%	52,661	2.48%
61-120 days ago	112,535	1.78%	25,742	1.88%	69,764	1.67%	42,771	2.01%
121-364 days ago	89,006	1.41%	20,971	1.53%	61,231	1.46%	27,775	1.31%
365+ days ago	11,470	0.18%	2,531	0.18%	8,380	0.20%	3,090	0.15%

4.2.2. Web Analytic Results for ‘Bounce Rate’

The ‘Bounce rate’ is the percentage of single-page visits or visits that resulted in visitor’s leaving the site from the entrance (landing) page. The metric is used to measure visit quality e.g. a high bounce rate would suggest that the B2C site’s entrance pages aren't relevant to the visitors. The general viewpoint is that the more relevant (or compelling) the landing pages the more visitors are envisaged to stay on the B2C site. Tailoring landing pages to keywords for and campaigns for example, is one method practitioner use to minimize bounce rates. Table 10 demonstrates a large variance and diversity in ‘bounce rate’ statistics exists with reference to both (1) various scenarios and even amongst (2) different URL’s that visitors may arrive at from the Google search engine to perform a similar task, e.g. making a Short-Haul booking. The large variances in raw data suggest poor consistency in ‘visit quality’ for the different booking scenarios. Reverting back to the Modified Audit Matrix, the disparity in results suggests poor consistency of “the consistency of visual impact of the site with the brand” for the different scenarios. In layman terms, a visitor arriving on short-haul section of the booking website may more quickly recognize the airlines brand than if he/she were arriving on the long-haul section of the booking website.

Table 10 - Web Analytic Results for ‘Bounce Rate’

URL	Overall Bounce Rate	Booking Flights	Booking Holidays	Booking Short-Haul	Booking Long-Haul
Splash Page	85.09%	73%	12%	10%	63%
OffspringSite	28.74%	13%	15%	11%	3%
ShortHaulBooking	75.26%	39%	36%	4%	35%
ShortHaulBooking	21.87%	5%	17%	3%	2%
ShortHaulBooking	9.84%	1%	9%	0%	1%
LongHaulBooking	25.38%	6%	20%	2%	4%
LongHaulBooking	48.04%	34%	14%	27%	7%
HolidayBooking	11.62%	10%	2%	5%	5%
HolidayBooking	14.16%	13%	1%	8%	5%
HolidayBooking	1.12%	0%	1%	0%	0%

4.2.3. Web Analytic Results for ‘Length of Visit’

The length of a visit is defined by the “elapsed time between page views” with the last page of a visit not being recorded as there is no subsequent page view. The ‘Length of a Visit’ is a measure of visitor quality and is based on the premise that a large number of lengthy visits would suggest that visitors interact more extensively with your site. Given that individual visit lengths can be perturbed by other factors (e.g. process efficiency of the visitor, speed of the visitor’s internet connection, etc), the ‘Average Time on Site’ based on the individual visit length is a stronger measure of overall visit quality and therefore a better score for the purposes of consistency. Table 11 simply demonstrates visitors typically spend longer making holiday bookings and long-haul bookings as compared to short-haul bookings. This is comprehendible given that holiday & long-haul bookings typically require a visitor to complete a greater number of data fields, experience more processes and it also can be assumed users typically place more carefully complete these bookings due to the greater distance and cost of travel. Incidentally Table 11 which demonstrates poor consistency with respect to "length of visit" may need to be analyzed in greater detail. In particular, the assertion that there exists inconsistency with respect to "value-add to the experience by graphics, collaterals and multimedia" maybe erroneous.

Table 11 - Web Analytic Results for 'Length of Visit'

Length of Visit	Visits	Overall	Booking Flights	Booking Holidays	Booking Short-Haul	Booking Long-Haul
0-10 seconds	4,626,497	73.29%	52%	28%	23%	1%
11-30 seconds	145,064	2.30%	2%	2%	0%	0%
31-60 seconds	181,709	2.88%	2%	0%	0%	0%
61-180 seconds	409,216	6.48%	41%	1%	0%	0%
181-600 seconds	473,855	7.51%	1%	1%	0%	98%
601-1,800 seconds	315,326	5.00%	2%	68%	26%	22%
1,801+ seconds	160,788	2.55%	1%	0%	0%	0%

4.2.4. Web Analytic Results for 'Loyalty'

Loyalty is defined by an aggregate score of the number of multiple visits made by visitors. It maybe suggested that 'loyal visitors' are those that are frequently and highly engaged with the brand and therefore likely to demonstrate a higher number of multiple visits. Table 12 demonstrates that the majority of visitors (~22%) have only visited the site once e.g. new visitors. With reference to the consistency of OUE, there is greater interest in the latter, e.g. the 78% of returning visitors or those with multiple visits. In particular, the interest lies in the distribution of multiple visits with reference different scenarios. For example, most visitors booking long-haul flights visit the site 3 times where as most visitors booking short-haul flights visit 26 times. Taken at face value this represents inconsistency in 'loyalty' and identifies to the airline that more may need to be done to the site for it to deliver on the "perceived promise of the brand" with respect to long-haul flights.

Table 12 - Web Analytic Results for 'Loyalty'

Number of Visits	Visits	Percentage of all visitors	Booking Flights	Booking Holidays	Booking Short-Haul	Booking Long-Haul
1 times	1,381,000	21.88%	829,011	551,989	694,066	134,945
2 times	573,387	9.08%	422,341	151,046	249,550	172,791
3 times	368,197	5.83%	74,756	293,441	47,584	27,172
4 times	274,314	4.35%	57,215	217,099	41,298	15,917
5 times	218,641	3.46%	46,503	172,138	30,011	16,492
6 times	181,061	2.87%	44,228	136,833	36,888	7,341
7 times	154,910	2.45%	37,088	117,822	18,961	18,127
8 times	136,116	2.16%	30,313	105,803	18,010	12,303
9-14 times	581,510	9.21%	128,652	452,858	92,079	36,572
15-25 times	595,313	9.43%	146,757	293,515	86,804	59,954
26-50 times	619,625	9.82%	131,418	488,207	94,254	37,164
51-100 times	524,208	8.30%	118,580	405,628	68,447	50,133
101-200 times	380,111	6.02%	84,693	295,418	46,816	37,877
201+ times	324,062	5.13%	67,458	256,604	48,707	18,751

4.2.5. Web Analytic Results for 'Depth of Visit'

The 'Depth of Visit' is a defined an aggregate score of the number of page views per visit and is a measure of visit quality. i.e. a large number of high page views per visit suggests that visitors interact extensively with the B2C site. The distribution of visits enables the ability to identify whether a few visits are skewing average page views per visit or whether visits actually result in a high number of pages being viewed. Table 13 demonstrates that ~72% users only view a total of 1 page when they visit the test B2C site. That 58% of all visits which result in 1 page viewed are related to Booking Flights and that 42% are related to Booking Holidays. Further, the 58% is composed of 56% when that 1 page viewed is related to booking a long-Haul flight and only 2% where that 1 page viewed is concerned with booking a short-haul flight. While this description is important to understand that statistics, what is key is that there exists a large variance in 'depth of visit' across the different scenarios. What this suggests is that there inconsistency with respect to the visitors interaction with the site. Now, one may argue that this inconsistency maybe just due to the fact that a larger number of pages are required to process say, a long-haul booking than compared to a short-haul. That maybe true, however given the extremely large variance (or inconsistency) of 52% vs. 2% it suggests other factors are at play unless ofcourse the long-haul booking process if 25x more lengthy than the short-haul booking process. It must be noted that a large 'depth of visit' is not necessarily a positive aspect for a site as it may indicate the visitors has spent searching a number of pages before he/she could complete the intended task (e.g. booking a flight). Applying this to the notion of 'consistency of OUE' this discrepancy may then provide further grounding that the booking scenarios are in-consistent with each other as the average user maybe applying similar rules to the long-haul booking section as used in the short-haul booking. This assertion however will require further analysis regarding the break-down of web traffic during the same period with respect to long-haul vs. short-haul sections of the site,

Table 13 - Web Analytic Results for 'Depth of Visit'

Depth of Visit	Visits	Percentage of all visitors	Booking Flights	Booking Holidays	Booking Short-Haul	Booking Long-Haul
<1 pages	18,273	0.29%	90%	10%	28%	63%
1 pages	4,525,656	71.69%	58%	42%	2%	56%
2 pages	644,377	10.21%	9%	91%	2%	7%
3 pages	300,197	4.76%	75%	25%	34%	41%
4 pages	188,425	2.98%	93%	7%	80%	12%
5 pages	131,951	2.09%	7%	93%	0%	7%
6 pages	94,696	1.50%	32%	68%	22%	10%
7 pages	71,238	1.13%	45%	55%	17%	29%
8 pages	55,505	0.88%	7%	93%	3%	4%
9 pages	44,621	0.71%	45%	55%	24%	22%
10 pages	36,143	0.57%	99%	1%	39%	60%
11 pages	29,440	0.47%	4%	96%	2%	2%
12 pages	24,258	0.38%	41%	59%	31%	10%
13 pages	19,953	0.32%	68%	32%	18%	51%
14 pages	16,505	0.26%	4%	96%	0%	4%
15 pages	13,905	0.22%	31%	69%	20%	11%
16 pages	11,838	0.19%	36%	64%	4%	32%
17 pages	9,984	0.16%	32%	68%	20%	11%
18 pages	8,677	0.14%	57%	43%	48%	9%
19 pages	7,305	0.12%	54%	46%	22%	32%
20+ pages	59,508	0.94%	26%	74%	3%	23%

4.3. OBTAINING INDEXED UE SCORES

For each record of data, a quotient of the total is obtained and multiplied by 100 to give an indexed score. Obtaining indexed user-experience (UE) scores in this way ensures raw data can be compared against each other for the purposes of assessing consistency. For example, juxtaposing the fact that '25% of visitors returned to the test case B2C site less than 3 days ago' against '32% of all visitors made 3 visits' during the sample period would be incomparable and analysis would provide little intelligence. The parameters for indexation are highly debatable (e.g. choosing a quotient of the total is arbitrary) and future work, based on sufficient justification, may choose to adjust or skew these parameters and provide a different format for indexation. Different scores maybe also be pegged categorically or weighted.

4.3.1. Indexed UE scores for ‘Visitor Recency’

The quotient of Visitor Recency scores was derived by taking the individual number of visitors for each Recency category, dividing this by the total number of ‘visitors’ (for that particular Recency category) and multiplying by 100. This was repeated for each Recency category for both OUE issues defined in 3.5.3, e.g. Booking Flights vs. Holidays and Booking Long-haul vs. Short Haul Flights. It was observed 3,813,523 visited the B2C site “0 days ago” for just booking flights and 823,044 visitors for just booking holidays. Accordingly, the total number of visitors equates to 4,636,567. Expressing 3,813,523 as a percentage of the total gives 82% and 823,044 gives 18% which define the respective index scores for that category. To illustrate the importance of normalizing the data set, a graph of the indexed scores has been plotted in Fig. 6. The correlation between the plotted lines is what helps define the consistency as per the framework argued in this study.

Table 14 - Indexed UE scores for ‘Visitor Recency’

Last Visit	Booking Flights Only		Booking Holidays		Booking Short-Haul		Booking Long-Haul	
	Visits	Indexed Score	Visits	Indexed Score	Visits	Indexed Score	Visits	Indexed Score
0 days ago	3,813,523	82	823,044	18	2,626,174	63	1,187,349	56
1 days ago	689,950	82	154,416	18	437,476	10	252,474	12
2 days ago	312,667	83	62,733	17	219,995	5	92,672	4
3 days ago	216,668	82	47,871	18	158,647	4	58,021	3
4 days ago	146,973	81	35,421	19	84,420	2	62,553	3
5 days ago	114,744	81	27,407	19	57,718	1	57,026	3
6 days ago	97,820	81	22,297	19	53,356	1	44,464	2
7 days ago	75,040	82	17,012	18	51,910	1	23,130	1
8-14 days ago	270,544	83	57,283	17	154,652	4	115,892	5
15-30 days ago	218,752	83	46,143	17	113,661	3	105,091	5
31-60 days ago	142,760	83	29,822	17	90,099	2	52,661	2
61-120 days ago	112,535	81	25,742	19	69,764	2	42,771	2
121-364 days ago	89,006	81	20,971	19	61,231	1	27,775	1
365+ days ago	11,470	82	2,531	18	8,380	0	3,090	0

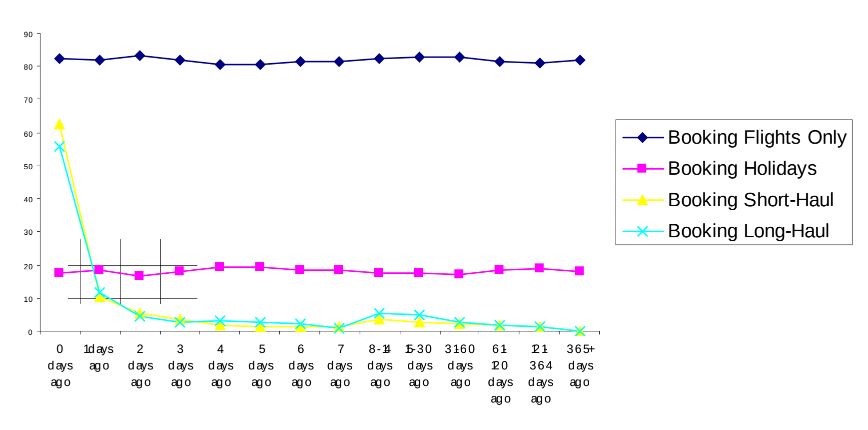

Figure 6 – Indexed UE scores

4.3.2. Indexed UE scores for 'Bounce Rate'

Table 15 - Indexed UE scores for 'Bounce Rate'

URL	Bounce Rate	**Booking Flights**	**Booking Holidays**	**Booking Short-Haul**	**Booking Long-Haul**
Splash Page	85.09%	73	12	10	63
OffspringSite	28.74%	13	15	11	3
ShortHaulBooking	75.26%	39	36	4	35
ShortHaulBooking	21.87%	5	17	3	2
ShortHaulBooking	9.84%	1	9	0	1
LongHaulBooking	25.38%	6	20	2	4
LongHaulBooking	48.04%	34	14	27	7
HolidayBooking	11.62%	10	2	5	5
HolidayBooking	14.16%	13	1	8	5
HolidayBooking	1.12%	0	1	0	0

4.3.3. Indexed UE scores for 'Loyalty'

Table 16 - Indexed UE scores for 'Loyalty'

Number of Visits	**Visits**	**Percentage of all visitors**	**Booking Flights**	**Booking Holidays**	**Booking Short-Haul**	**Booking Long-Haul**
1 times	1,381,000	21.88%	60	40	50	10
2 times	573,387	9.08%	74	26	44	30
3 times	368,197	5.83%	20	80	13	7
4 times	274,314	4.35%	21	79	15	6
5 times	218,641	3.46%	21	79	14	8
6 times	181,061	2.87%	24	76	20	4
7 times	154,910	2.45%	24	76	12	12
8 times	136,116	2.16%	22	78	13	9
9-14 times	581,510	9.21%	22	78	16	6
15-25 times	595,313	9.43%	25	75	15	10
26-50 times	619,625	9.82%	21	79	15	6
51-100 times	524,208	8.30%	23	77	13	10
101-200 times	380,111	6.02%	22	78	12	10
201+ times	324,062	5.13%	21	79	15	6

4.3.2. Indexed UE scores for 'Depth of Visit'

Table 17 - Indexed UE scores for 'Depth of Visit'

Depth of Visit	Visits	Percentage of all visitors	Booking Flights	Booking Holidays	Booking Short-Haul	Booking Long-Haul
<1 pages	18,273	0.29%	90	10	28	63
1 pages	4,525,656	71.69%	58	42	2	56
2 pages	644,377	10.21%	9	91	2	7
3 pages	300,197	4.76%	75	25	34	41
4 pages	188,425	2.98%	93	7	80	12
5 pages	131,951	2.09%	7	93	0	7
6 pages	94,696	1.50%	32	68	22	10
7 pages	71,238	1.13%	45	55	17	29
8 pages	55,505	0.88%	7	93	3	4
9 pages	44,621	0.71%	45	55	24	22
10 pages	36,143	0.57%	99	1	39	60
11 pages	29,440	0.47%	4	96	2	2
12 pages	24,258	0.38%	41	59	31	10
13 pages	19,953	0.32%	68	32	18	51
14 pages	16,505	0.26%	4	96	0	4
15 pages	13,905	0.22%	31	69	20	11
16 pages	11,838	0.19%	36	64	4	32
17 pages	9,984	0.16%	32	68	20	11
18 pages	8,677	0.14%	57	43	48	9
19 pages	7,305	0.12%	54	46	22	32
20+ pages	59,508	0.94%	26	74	3	23

4.4. MEASUREMENT OF CONSISTENCY

As stipulated in the methodology, the final part of the computation involves calculating the correlation coefficient for each permutation in scenario. That is, to establish consistency evaluation over how different or similar each data set is for a given scenario. The correlation coefficient ranges from +1 (indicating a perfect positive linear relationship) to -1 (indicating a perfectly negative linear relationship). It is important to note the aim of this study is not to proactively search for a relationship. Instead the interest lies in describing it. A plausible hypothesis is that where poor correlation exists (e.g. correlation coefficient values are between 0 and 0.25) it can be concluded that based on that particular measure, the OUE is extremely different for that given scenario. Vice-versa, where strong correlation exists (e.g. correlation coefficient values are between 0 and 0.2 or 0 and -2) the OUE is similar. Reverting back to the original research questions, there is an attempt to answer based on user behavior, how consistent the OUE is for (1) Booking Long-Haul vs. Short Haul flights and (2) Booking Flight vs. Holidays.

4.4.1. Correlation table for 'Visitor Recency'

Table 18 - Correlation table for 'Visitor Recency'

	Booking Holidays	Booking Short-Haul	Booking Long-Haul	Booking Flights Only
Booking Holidays	x	-0.200	-0.199	-1.000
Booking Short-Haul	-0.200	X	0.997	0.200
Booking Long-Haul	-0.199	0.997	X	0.199
Booking Flights Only	-1.000	0.200	-0.199	x

The correlation table for 'Vistor Recency' (produced in Table ##) suggests that, based on the measure of 'Visitor Recency', there is a:

- Strong correlation between Booking Long-Haul vs. Short Haul flights (e.g. ~1).
- Poor correlation exists between Booking Holidays and booking Long-Haul flights (~-0.2)
- Poor correlation exists between Booking Holidays and booking short-haul flights (~-0.2).

4.4.2. Correlation table for 'Bounce Rate'

Table 19 - Correlation table for 'Bounce Rate'

	Booking Holidays	Booking Short-Haul	Booking Long-Haul	Booking Flights Only
Booking Holidays	1.000	0.341	0.477	0.940
Booking Short-Haul	0.341	1.000	0.046	0.365
Booking Long-Haul	0.477	0.046	1.000	0.150
Booking Flights Only	0.940	0.365	0.150	1.000

The correlation table for 'Bounce Rate' (produced in Table ##) suggests that, based on the measure of 'Bounce Rate' that:

- Poor correlation between Booking Long-Haul vs. Short Haul flights (~0)
- Poor correlation between Booking Holidays and booking Long-Haul flights (~-0.5)
- Poor correlation between Booking Holidays and booking short-haul flights (~-0.35)

4.4.3. Correlation table for 'Loyalty'

Table 20 - Correlation table for 'Loyalty'

	Booking Holidays	Booking Short-Haul	Booking Long-Haul	Booking Flights Only
Booking Holidays	1.000	-1.000	0.949	0.801
Booking Short-Haul	-1.000	1.000	-0.949	-0.801
Booking Long-Haul	0.949	-0.949	1.000	0.572
Booking Flights Only	0.801	-0.801	0.572	1.000

The correlation table for 'Loyalty' (produced in Table 20) suggests that, based on the measure of 'Loyalty', there is:

- Strong negative correlation between Booking Long-Haul vs. Short Haul flights (~-1)
- Strong correlation exists between Booking Holidays and booking Long-Haul flights (~1)
- Strong negative correlation exists between Booking Holidays and Booking short-haul flights (~-1).

4.4.4. Correlation table for ''Depth of Visit'

Table 21 - Correlation table for ''Depth of Visit'

	Booking Holidays	Booking Short-Haul	Booking Long-Haul	Booking Flights Only
Booking Holidays	1.000	-1.000	0.749	0.750
Booking Short-Haul	-1.000	1.000	-0.749	-0.750
Booking Long-Haul	0.749	-0.749	1.000	0.123
Booking Flights Only	0.750	-0.750	0.123	1.000

The correlation table for 'Depth of Visit' (produced in Table 21) suggests that, based on the measure of 'Depth of Visit', there is;

- Strong negative correlation between Booking Long-Haul vs. Short Haul flights (e.g. ~-0.75).
- Strong correlation exists between Booking Holidays and booking Long-Haul flights (~0.75)
- Strong negative correlation exists between Booking Holidays and booking short-haul flights (~-1).

CHAPTER 5: DISCUSSION OF RESULTS

5.1. CHAPTER OVERVIEW

This purpose of this chapter is to summarize significant findings of the study and reiterate the implications of these findings in terms of both academic work and business practice. Findings of this study are also compared to prior research and discussed.

5.1. Chapter Overview
5.2. Significant Findings and Implications
5.3. Implications for business practice

5.2. SIGNIFICANT FINDINGS AND IMPLICATIONS

To derive findings from the analysis, original scenarios identified in 3.5.3 have been reverted to and results re-tabulated. For example, in each of the two scenarios, results have been juxtaposed against both the original *RUEA Audit Statement* and the *Modified Audit Statement*.

5.2.1. Booking flights vs. holiday packages

As booking long-haul and short-haul flights invite the user through different processes, the consistency scores have been analyzed separately in (1) and (2).

(1) Booking Long-Haul flights vs. holiday packages

Table 22 - Booking Long-Haul flights vs. holiday packages

Scenario	Rubinoff's OUE Audit	Modified OUE Audit	Web Analytic Measure	Result	
Booking Holidays and Booking Long-Haul flights	"The site provides visitors with an engaging and memorable experience"	"The frequency with which visitors return to your site indicates the site provides visitors with an engaging and memorable experience"	Visitor Recency	Poor correlation	~-0.2
Booking Holidays and Booking Long-Haul flights	"The visual impact of the site is consistent with the brand identity"	"The number of single page visits on your site indicates how extensively visitors interact with your brand"	Bounce Rate	Poor correlation	~-0.5
Booking Holidays and Booking Long-Haul flights	"The site delivers on the perceived promise of the brand"	"The number of multiple visits and new visitors indicates the site delivers on the perceived promise of the brand"	Loyalty	Strong correlation	~1
Booking Holidays and Booking Long-Haul flights	"The site leverages the capabilities of the medium to enhance or extend the brand"	"The number of visits with high page views acknowledges that the site leverages the capabilities of the medium to enhance or extend the brand"	Depth of Visit	Strong correlation	~0.75

Table 22 suggests that visitors experience a different Online User Experience when Booking Long-Haul flights than when making Holiday package bookings. While visitors exhibit similar levels of 'loyalty' and find both booking scenarios to 'leverage the brand experience' of the B2C site, poor negative correlation with the 'Visitor Recency' and 'Bounce Rate' score indicates visitors find the long-haul product to provide a far more engaging experience and consistent with brand identity. These are reasonable comments given that the holiday packages website is a third-party website and does not follow similar conventions or processes than either booking flights. Also, it is almost impossible to arrive at the holiday packages site through a search engine and this fact will impact on the 'bounce rate' score. We expected 'loyalty' to remain unchanged as visitors are typically up-sold in making a holiday package booking and are exposed to the corporate logo of the test B2C site throughout the online user experience.

(2) Booking Short-Haul flights vs. holiday packages

Table 23 - Booking Short-Haul flights vs. holiday packages

Scenario	Rubinoff's OUE Audit	Modified OUE Audit	Web Analytic Measure	Result	
Booking Holidays and Booking short-haul flights	"The site provides visitors with an engaging and memorable experience"	"The frequency with which visitors return to your site indicates the site provides visitors with an engaging and memorable experience"	Visitor Recency	Poor correlation	~-0.2.
Booking Holidays and Booking short-haul flights	"The visual impact of the site is consistent with the brand identity"	"The number of single page visits on your site indicates how extensively visitors interact with your brand"	Bounce Rate	Poor correlation	~-0.35
Booking Holidays and Booking short-haul flights	"The site delivers on the perceived promise of the brand"	"The number of multiple visits and new visitors indicates the site delivers on the perceived promise of the brand"	Loyalty	Strong negative correlation	~-1
Booking Holidays and Booking short-haul flights	"The site leverages the capabilities of the medium to enhance or extend the brand"	"The number of visits with high page views acknowledges that the site leverages the capabilities of the medium to enhance or extend the brand"	Depth of Visit	Strong negative correlation	~-1.

Table 23 suggests demonstrates visitors experience a completely different Online User Experience when Booking Short-Haul flights than when making Holiday package bookings. While visitors exhibit dissimilar levels of 'loyalty' and find both booking the short-haul booking scenario to 'leverage the brand experience' far greater than booking a holiday package, strong negative correlation with the 'Visitor Recency' and 'Bounce Rate' score indicates visitors find the short-haul product to provide a far more engaging experience and consistent with the airline's brand identity. Again, these are reasonable comments given that the short-haul product requires very limited information to complete a booking and usually consists of point-to-point destinations. Booking a holiday package on the other hand requires the visitor to learn a different booking process (as it's a third-party website and does not follow similar conventions or processes than booking flights). We expected 'loyalty' to be vastly different as visitors who purchase short-haul fares would include the large number of domestic bookings who do not typically purchase accommodation which would require them to visit the holiday packages site. What is of surprise is that the figures suggest visitors experience a much stronger brand identity when making a short-haul booking than a holiday package given that the corporate logo and website colors remain similar.

5.2.2. Booking Long-Haul vs. Short Haul flights

Table 24 - Booking Long-Haul vs. Short Haul flights

Scenario	Rubinoff's OUE Audit	Modified OUE Audit	Web Analytic Measure	Result	
Booking Long-Haul vs. Short Haul flights	"The site provides visitors with an engaging and memorable experience"	"The frequency with which visitors return to your site indicates the site provides visitors with an engaging and memorable experience"	Visitor Recency	Strong correlation	~1.
Booking Long-Haul vs. Short Haul flights	"The visual impact of the site is consistent with the brand identity"	"The number of single page visits on your site indicates how extensively visitors interact with your brand"	Bounce Rate	Poor correlation	0
Booking Long-Haul vs. Short Haul flights	"The site delivers on the perceived promise of the brand"	"The number of multiple visits and new visitors indicates the site delivers on the perceived promise of the brand"	Loyalty	Strong negative correlation	~-1
Booking Long-Haul vs. Short Haul flights	"The site leverages the capabilities of the medium to enhance or extend the brand"	"The number of visits with high page views acknowledges that the site leverages the capabilities of the medium to enhance or extend the brand"	Depth of Visit	Strong negative correlation	~-0.75.

Table 24 suggests visitors generally experience a different Online User experience when booking Short-Haul flights than when booking long-haul flights. The negatively skewed correlation Loyalty consistency scores demonstrate that visitor's exhibit a far greater 'loyalty' to booking short-haul flights with this airline than booking long-haul flights. In practice, this would indicate visitors are returning to this airline for domestic fares but for booking long-haul flights, visitors maybe shopping around perhaps at websites of competitor airlines or travel agents. That said, given the 'Visitor Recency' is positively skewed it indicates visitors are still constantly returning to the site, which may point to visitors price-checking for long-haul fares. The strong negative correlation for 'Depth of Visit' demonstrates that visitors do not find the website to leverage the capabilities of the online site when it comes to booking long-haul fares. It must be acknowledge that visitors are able to book multi-stop short-haul fares on the website but for long-haul fares multi-stop bookings require a phone booking and a service fee.

5.3. IMPLICATIONS FOR BUSINESS PRACTICE

The findings, based on the branding element alone, suggest there is inconsistency between the average visitors' Online User Experience when making a short-haul booking to making a long-haul booking to building a holiday package. The in-consistency would suggest the average user would to find it a challenge (or a learning process) if he/she were to change routes or destinations or choose to purchase additional products (e.g. add accommodation to a simple flight booking). Making recommendations on how to improve consistency is beyond the scope of this study but the implications for business practice are clear: the need to improve consistency by perhaps integrating the short-haul, long-haul and holiday-package booking processes.

CHAPTER 6: CONCLUSION

6.1. CHAPTER OVERVIEW

The purpose of this chapter is to summarize the findings of the study and the short-falls encountered. For example, a re-cap into how particular elements in the framework remains incomplete for analysis because there exist no available web analytic measures that can effectively represent them. Some discussion in this section focuses on how limitation in the models ability to assess OUE impacts in determining consistency. Finally, the wider discussion addresses the limitations of the research undertaken and follows onto making succinct recommendation for future research with a particular emphasizes for refining the framework developed.

6.1. Chapter Overview
6.2. Summary of Research Findings
6.3. Limitations of the Research
6.4. Recommendations for Future Research

6.2. SUMMARY OF RESEARCH FINDINGS

This paper has documented the journey of attempting to develop a framework to measure the consistency of Online User Experience. This section aims to consolidate and elaborate on comments that reflect the research process. These findings and conclusions are different to the findings from the data which were covered in Section 5.

6.2.1. Reflection on development of the OUE framework

The research experience in developing the OUE framework suggests considerably more effort needs to be spent in identifying specific constructs in web assessment methods and aligning these against measurements that can be derived from web analytics. Unfortunately, the body of knowledge that currently exists within the area of web assessment is composed of either largely qualitative studies (Evans & King, 1999; Niamh & Jurek, 2006) or a dispersion of custom experiential scales (Ozok & Salvendy, 2000, 2001). There are limited popular constructs or methods that would acknowledge researchers have reached some consensus over web assessment for a specific aspect or element of OUE. On the other side of the fence, is a plethora of practioner based methods (Gaffney, 2005; Rubinoff, 2004) that are often found in whitepapers (authored by usability consultants) but again, there exists limited consensus even amongst practioners over methods for measuring OUE. This study may have performed a highly rudimentary task in adjoining findings from published literature in web assessment to web analytic methods but given the fragmented state of OUE research, it is arguable that this paper has actually attempted to consolidate web assessment methods, even if this was in an attempt to develop a novel framework to explore "consistency". Therefore should this work be used to build a more sophisticated framework to measure consistency of OUE, it would be prudent that a survey of the latest quantitative web assessment methods is re-taken and the framework is replenished with these. There is evidence to suggest that web assessment methods found in academic literature are increasingly going to harness the power of web analytics and this tool will no longer remain a beacon just for practioners (Frew, 2004; Welling & White, 2006). This is convenient given the approach taken in this study. In particular, deliberation over how web analytics maybe sufficed to provide evidence-based web assessment will only lead to a more rigorous framework should future research decide to take the approach this study has taken in developing a framework. That is, if academic researchers begin to use web analytics to assess and model specific aspects of the website and thereby OUE, a quantitative framework can be readily developed and the effort spent on carefully investigating how consistency of OUE may be derived.

6.2.2. Reflection on development of a consistency score

It may be argued that this study has taken an extremely arbitrary approach by using correlation to assess the deviance in UE scores. However, this method is consistent with published literature (Ozok & Salvendy, 2000, 2001) even if it performs correlation on data that has been derived from web analytics rather than user-surveys. In developing a method of consistency of OUE scoring however both (Ozok & Salvendy, 2001) and this study have failed to provide any allowance for 'legitimate factors' that may skew consistency. For example, a visitor who is responsible for making multiple short-haul bookings (e.g. for their family) is legitimately going to take a longer time than a visitor is who making say, a single long-haul booking. Now, with respect to the scoring – this would affect the 'length of visit' analytic and if in a given period this happened a large number of times, skew the UE score for "Graphics, collaterals and multimedia add value to the experience" suggesting that the long-haul site's OUE is inconsistent with the short-haul booking. To overcome this, there needs to be a need for normalizing this data against say against sales data. Therefore, reverting to the original example given, if based on revenue it was reported that 4 short-haul bookings were made, the total 'length of visit' would be divided by 4 and this would provide equal OUE comparison with the visitor making a long-haul booking. There are number of intelligent ways to provide an allowance for legitimate factors such as the one described though normalization is a strong one.

6.2.3. Usability testing cannot be replaced by an OUE framework

"There is a temptation to believe that web analytic technology can replace proven usability testing, which simply is not true" (Wiggins, 2006). Most authors will argue that web analytics cannot provide the level of insight that usability testing is able to accomplish irrespective of how sophisticated the measurements are (Reed & Groth, 2008; Rubinoff, 2004; Wiggins, 2006). This implies that existing and future work that engages in building a consistency of OUE framework will always be second to proven visual checks by web designers, second to QA checks against web style guides by QA Analysts and second to formalized testing procedures by Test Analysts. This is acceptable and known. There continues to be a growing number papers that agree that "usability testing combined with web analytics, customer satisfaction information, and a/b optimization, enable usability expenses to be cut dramatically, and purportedly without loss in quality" (Wiggins, 2006; Xu et al., 2003).

6.3. LIMITATIONS OF THE RESEARCH FINDINGS

Due to the scope of the work undertaken and the formal expectation of the scope of this study, the research is unfortunately fraught by limitations.

6.3.1. Incomplete OUE framework

To limit scope this study has chosen to focus on a particular RUEA element "Branding" and essentially ignored the development other RUEA elements. The findings are therefore highly skewed towards this single element "Branding" and this fails to represent the practical mix of elements which was initially envisaged. The data and findings are also subject to change should the OUE framework be rendered complete by binding web analytics measurement to other RUEA elements and the data analysis is repeated.

6.3.2. Linking Modified UE statements to single web analytic measurements

For simplicity sake modified UE statements were intentionally linked to single web analytics measurements e.g. in assessing an "engaging and memorable experience" only the analytic "number of returning users" was used. However, it is difficult to believe that one single web analytic measurement may suffice in describing a UE factor/statement fully. More so, there is no robust evidence to suggest this is the case and based on the experience gained in this framework development exercise it seems unlikely. Instead a better proposition is that certain factors/statements may benefit from several web analytics measurements, e.g. a composition of measurements with different weightings. How these weightings are established is a topic for future study but structural equation modeling to identify causal relationships maybe a starting point – the use of SEM is discussed in 6.4.2.

6.3.3. Limitations due to issues affecting data integrity

It should be noted there are an infinite number of instances and causes that could have perturbed the web analytics data (and resulted findings) and therefore, unless repeating patterns exist, the findings should be digested with these factors in mind. For example, as Google Analytics identifies visitors by IP address (and no other information) repeat visitors may not be correctly identified and may count as distinct visitors depending on their number of visits. This may due to a range of factors, e.g. if these visitors work in an environment where IP addresses are allocated dynamically or if they are using multiple devices to connect to the site or if they have simply deleted cookies on their browser cache. Such issues raise limitations over the applicability of using the web analytics data without further processing and analysis.

6.3.4. Limitations due to the nature of assumptions made

To ensure simplicity in the data analysis some assumptions were made that may not hold true in reality. For example, in analyzing the consistency of "Loyalty" data it was assumed that irrespective of the product (Short Haul Flights, Long Haul Flights or Holidays) each will accrue the same number of multiple visits. This is not necessarily true. For arbitrary reasons, it can be safely hypothesized that consumer patterns exists in the travel industry and these may vary over different parts of a single year – the same period of the data used for analysis. For example, during the Christmas Holiday period visitors are likely to choose the Holiday product whereas during the end of a fiscal year increased corporate travel may dominate the short haul sector. The data presented already indicates that short-haul flights are booked more frequently than long-haul and therefore a qualifying assumption could be that loyalty scores for short-haul should be higher than those for long-haul? Without acknowledging for pre-existing patterns and making adjustments, there are limitations introduced with the integrity of the analysis.

6.3.5. Limitations of the statistical analysis

A key limitation in computing a Pearson correlation coefficient as measure of consistency is that a linear relationship is automatically assumed and this is not known to be necessarily true. User Experience scores may vary differently at different ends of the spectrum due to factors discussed in (but not limited to) 6.3.4 and 6.3.5.

6.4. CONTRIBUTIONS OF THE STUDY

A direct outcome of this study is a deliverable that provides a prototype framework for measuring consistency of "branding" and makes suggestions for measuring the consistency of OUE overall of a given B2C site. This dissertation documents the process of developing such a measure/construct/framework and provides some, even if general, recommendations towards improving consistency of online user experience using results from the framework to the case of the test B2C site. The framework also contributes to existing body of work by proposing a novel framework. Due to the limitation of a single semesters worth of study and there being little founding work in this area, it can be acknowledged that the rigor of the suggested framework is perhaps weak. However, the work done provides a basis for future research which is discussed in the next sub-section 6.5.

6.5. RECOMMENDATIONS FOR FUTURE RESEARCH

There are two key practical recommendations to enhance the pace and quality of a future OUE framework should this work be chosen as a basis or not. However, a fundamental task of any future work is to ensure a significantly more robust and comprehensive investigation of the various OUE factors is performed. This would enable a more solid validation between different elements, e.g. the relationship between graphic, collateral and multimedia elements can be regarded as particularly tenuous in its current state. Unfortunately, the lack of a validation cycle does not help this. Future work would benefit from a method to ensure data gathered can be corroborated against certain empirical findings, e.g. consistency between Element X and Element Y of Branding is unlikely to vary greater than value Z.

6.5.1. Development of an web Analytics API to model the methodology

This study has elected to extract a small amount of sample web analytic data, perform some rudimentary analysis and make judgments about the consistency of OUE based on this data. While this may be acceptable for model development and even repeatable – in practical terms, it is likely to be found to be a time-consuming process. The time taken to process the data would in-fact defeat the purpose of the analysis as web-analytic data is time-sensitive. Should be it undertaken by a commercial organization that wishes to measure "consistency of OUE" on its B2C website the cost (based on the time invested) would be too great. Accordingly, a better strategy maybe to develop an application programming interface (API) with the web analytics provider (e.g. Google Analytics) that imports the data into a warehouse and performs real-time analysis using the methodology demonstrated in this paper, e.g. to derive scores for the modified RUEA matrix, indexed scores and consistency calculations.

6.5.2. Examining dependencies between elements using SEM Analysis

The use of Structural Equation Modeling (SEM) to obtain a model that confirms relationships between important variables in the matrix could be a method of validating the OUE framework. Comparing relationships between different elements found in the paper against known and published results in other published work will enable us to validate the framework for measuring consistency against other models used for website analysis. We appreciate that SEM is a technique typically used for confirmatory rather than exploratory modeling e.g. theory testing vs. theory development, however at the time of writing a better technique could not be found given the relatively small size of the sample. We understand that SEM is a confirmatory technique emphasizing the need for the model to be specified correctly based on the type of analysis to be confirmed – in response to this requirement, future work would need to develop a model from previous work done and test perhaps several possible models. The SEM analysis process will use consist of two parts and use a specialized SEM analysis program, such as SPSS' AMOS for computational purposes. The first objective would be to obtain a structural model (e.g. path diagrams) to help demonstrate potential causal dependencies between variables. Secondly, the measurement model via Confirmatory factor analysis will confirm the relations between variables and their indicators. Again, estimated relationships from previous studies may be used to specify an initial model and clarify underlying relationships. Maximum likelihood Parameter estimation will be accomplished by comparing actual covariance matrices (representing the relationships between the different ‘evaluative points’) and the estimated covariance matrices (of the best fitting model) to obtain.

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APPENDIX

Overview of Google Analytics

Google Analytics (abbreviated GA) is a free service offered by Google that generates detailed statistics about the visitors to a website.

Caveats

- While Google Analytics is absolutely free of charge it is limited to 5 million page views a month.

Glossary of Google Analytics Terms/Definitions

Item	Definition
Page	A page is an analyst definable unit of content.
Page Views	The number of times a page (an analyst-definable unit of content) was viewed.
Visits/Sessions	A visit is an interaction, by an individual, with a website consisting of one or more requests for an analyst-definable unit of content (i.e. "page view"). If an individual has not taken another action (typically additional page views) on the site within a specified time period, the visit session will terminate.
Unique Visitors	The number of inferred individual people (filtered for spiders and robots), within a designated reporting timeframe, with activity consisting of one or more visits to a site. Each individual is counted only once in the unique visitor measure for the reporting period.
New Visitor	The number of Unique Visitors with activity including a first-ever Visit to a site during a reporting period.
Repeat Visitor	The number of Unique Visitors with activity consisting of two or more Visits to a site during a reporting period.
Return Visitor	The number of Unique Visitors with activity consisting of a Visit to a site during a reporting period and where the Unique Visitor also Visited the site prior to the reporting period.
Entry Page	The first page of a visit.
Landing Page	A page intended to identify the beginning of the user experience resulting from a defined marketing effort.
Exit Page	The last page on a site accessed during a visit, signifying the end of a visit/session.
Visit Duration	The length of time in a session. Calculation is typically the timestamp of the last activity in the session minus the timestamp of the first activity of the session.
Referrer	The referrer is the page URL that originally generated the request for the current page view or object.
Internal Referrer	The internal referrer is a page URL that is internal to the website or a web-property within the website as defined by the user.
External Referrer	The external referrer is a page URL where the traffic is external or outside of the website or a web-property defined by the user.
Search Referrer	The search referrer is an internal or external referrer for which the URL has been generated by a search function.
Visit Referrer	The visit referrer is the first referrer in a session, whether internal, external or null.
Original Referrer	The original referrer is the first referrer in a visitor's first session, whether internal, external or null.
Click-through	Number of times a link was clicked by a visitor.
Click-through Rate/Ratio	The number of click-through's for a specific link divided by the number of times that link was viewed.
Page Views per Visit	The number of page views in a reporting period divided by number of visits in the same reporting period.
Page Exit Ratio	Number of exits from a page divided by total number of page views of that page.

Single-Page Visits	Visits that consist of one page regardless of the number of times the page was viewed.
Single Page View Visits (Bounces)	Visits that consist of one page-view.
Bounce Rate	Single page view visits divided by entry pages.
Event	Any logged or recorded action that has a specific date and time assigned to it by either the browser or server.
Conversion	A visitor completing a target action.