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Aggregating Divergent Contexts in a Mobile Tourist Application

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Abstract

Purpose - Increasingly manufacturers of smartphone devices are utilising a diverse range of sensors. This innovation has enabled developers to accurately determine a user's current context. One area that has been significantly enhanced by the increased use of context in mobile applications is tourism. Traditionally tour guide applications rely heavily on location and essentially ignore other types of context. This has led to problems of inappropriate suggestions and tourists experiencing information overload. These problems can be mitigated if appropriate personalisation and content filtering is performed. This research proposes an intelligent context aware recommender system that aims to minimise the highlighted problems.

Design / Methodology / Approach - Intelligent reasoning was performed to determine the weight or importance of each different type of environmental and temporal context. Environmental context such as the weather outside can have an impact on the suitability of tourist attractions. Temporal context can be the time of day or season; this is particularly important in tourism as it is largely a seasonal activity. Social context such as social media can potentially provide an indication of the 'mood' of an attraction. These types of context are combined with location data and the context of the user to provide a more effective recommendation to tourists. The evaluation of the system is a user study that utilised both qualitative and quantitative methods, involving forty participants of differing gender, age group, number of children and marital status.

Findings - This study revealed that the participants selected the context based recommendation at a significantly higher level than either location based recommendation or random recommendation. It was clear from analysing the questionnaire results that location is not the only influencing factor when deciding on a tourist attraction to visit.

Research Limitations / Implications - In order to effectively determine the success of the recommender system, various combinations of contextual conditions were simulated. Simulating contexts provided the ability to randomly assign different contextual conditions to ensure an effective recommendation under all circumstances. This is not a reflection of the 'real world' because in a 'real world' field study the majority of the contextual conditions will be similar. For example, if a tourist visited numerous attractions in one day, then it is likely that the weather conditions would be the same for the majority of the day, especially in the summer season.

Practical Implications - Utilising this type of recommender system would allow the tourists to "go their own way" rather than following a prescribed route. By using this system, tourists can co-create their own experience using both social media and mobile technology. This increases the need to retain user preferences and have it available for multiple destinations. The application will be able to learn further through multiple trips and as a result the personalisation aspect will be incrementally refined over time. This extensible aspect is increasingly important as personalisation is gradually more effective as more data is collated.

Originality / Value - This paper contributes to the body of knowledge that currently exists regarding the study of utilising contextual conditions in mobile recommender systems. The novelty of the system proposed by this research is the combination of various types of temporal, environmental and personal context data to inform a recommendation in an extensible tourism application. Also, performing Sentiment Analysis on social media data has not previously been integrated into a tourist recommender system. The evaluation concludes that this research provides clear evidence for the benefits of combining social media data with environmental and temporal context to provide an effective recommendation.

Keywords: Recommender System, Tour Guide System, Mobile Tour Guide, Context Awareness, Social Media, Intelligent System

Paper Type: Research Paper

Introduction

The prevalence of the smartphone has had huge implications for travel planning activities during, before and after visiting a destination (Wang & Fesenmaier, 2013). Wang and Fesenmaier (2013) show that the planning process has become easier as a result of having ubiquitous access to the Internet using mobile devices. People can plan their holiday at any time, which has resulted in additional travel planning. The planning activity is also more flexible as a tourist can now incrementally plan during the actual holiday and easily respond to temporal difficulties (Buhalis & Foerste, 2013). The impact of mobile technology on tourism has been very significant. This technology has enabled users to find information conveniently, understand the geography of their current location/area, share their experiences and use as a tool for learning (Trakulmaykee, et al., 2013).

The widespread dissemination of smartphones has enabled an ever-growing minority of tourists to use mobile applications while visiting tourist destinations (Chon & Hojung, 2011). According to TripAdvisor, 60% of tourists have downloaded an app for tourism and 45% of tourists actively use these applications for decision-making (Lu, et al., 2015). These applications have become more beneficial for a tourist with the introduction of location sensing on mobile devices. This capability means that a mobile application can now estimate the user's current location in order to tailor services to their estimated needs. Tourists are receiving a rich, immersive and rewarding experience as a result of using mobile applications. These mobile applications range from mapping or navigation applications to tour guide applications (Schwinger, et al., 2008).

There is evidence that there is a large community of travellers who would like immediate information from other like-minded individuals (Pearce, 2011). This information could potentially be used to alter a tourist's itinerary in real-time. The tourist "on the move" makes many decisions based on social interactions, technology and environmental factors. These decisions are interdependent on various types of context (Hwang, et al., 2006). These social interactions could be from social media messages or social interactions with other travellers in a group. The mobile phone is one of the few devices that a tourist can store on their person and is the device of choice for real-time dissemination of messages. This real-time information support on smartphones allows tourists to more effectively make decisions such as solving situational problems, sharing experiences and storing memories (Lamsfus, et al., 2013). This can help the tourist remember the experience and also help inform other tourists about potential problems. The final factor influencing tourists' is environmental factors, these can often have a significant impact on the decision making process.

Tan et al. (2009) introduced a taxonomy of conceptual information named TILES (Temporal context, Identity context, Location context, Environmental context, Social context). The TILES concept has a significant influencing factor on the motivations of tourists. These conditions can be the basis of evaluating the performance of a mobile recommender system (Tan, et al., 2009). Temporal context could be the time of day or season; this is particularly important in tourism as it is a seasonal activity. Identity refers to the personalisation or profile aspect of the application, defining the user as a context. Location represents the location of the attractions or destinations and is one of the most widely used context types in tourism. Environmental context could be the weather outside and the impact this has on the availability of tourist attractions. Finally, the Social context relates to social media or the experience of like-minded tourists.

Mobile Recommender Systems

The evolution of recommender systems has been substantial in recent years. These systems are moving away from the crude rule based design to a more intelligent predictive model (Konstan & Riedl, 2012). Recommender systems use various types of contextual information and user interaction to personalise results to fit the user's needs (Baltrunas, et al., 2011). The information gathered by a system can be both explicitly asking user's to answer questions or implicitly gathering information from the user's interaction history (Schmidt-Belz, et al., 2002). Recommendation techniques can be broadly categorised into four areas, these are firstly collaborative filtering, secondly content based recommendation, thirdly knowledge based systems and finally hybrid recommenders.

Collaborative filtering takes into consideration the views/ratings of peers when deciding on recommendations; sometimes this is narrowed down into a specific demographic with similar interests (Herlocker, et al., 2012; Resnick, et al., 1994). This method is based largely on the social construct of 'word-of-mouth' where a person with similar interests to you makes a recommendation (Hill, et al., 1995). The techniques used have become more efficient in recent times and two defined approaches have been standardised as memory-based algorithms and model based techniques (Adomavicius & Tuzhilin, 2008; Baltrunas, et al., 2011).

Content based recommenders make decisions based on what the user has previously rated or what the user is currently viewing. In most areas this is requesting direct feedback from the user with a rating scale or a like/dislike button (Giordano, et al., 2012). Predictive models incorporating machine learning are often utilised to generate a user profile (Baltrunas & Amatriain, 2009). The main benefit of this type of recommendation model is that it does not suffer from the 'new-item' problem. This is the problem that an item is new and other users have not yet rated it or there is inadequate data (Jannach, et al., 2010). However, there is generally a lower accuracy with these recommendations compared to collaborative filtering and there is more likelihood for the content to be too similar and unsurprising (Baltrunas, et al., 2011).

Knowledge based systems are designed by a tourism domain expert and store recommendation rules to make inferences about the user's needs (Jannach, et al., 2010). These systems also store user interaction data to perform predictions that can help if similar behaviour is observed (Lops, et al., 2011). Unlike the other recommendation techniques, no user information is required for this type of system so they do not suffer with the cold-start problem (Baltrunas, et al., 2011). The cold-start problem is when recommendations are requested for items that are currently unrated in the current dataset (Schein, et al., 2002). Due to the immense amount of information required to be input by a domain expert, knowledge based systems can be very expensive to develop.

The Hybrid recommender is a combination of the collaborative filtering and content based recommendation techniques. These are used in conjunction to resolve the weaknesses in each of the techniques (Amatriain, et al., 2010). For example, a content based recommender would find it difficult to make a decision when there is no previous user data; in this regard collaborative filtering can provide initial data based on the user's demographic profile (Burke, 2002). Gavalas et al. (2011) discusses the unique problems presented by using recommendation in a mobility context. These problems include using the user's current context to provide an additional layer on information, however, opportunities are also presented in terms of direct communication for recommendations (Gavalas & Kenteris, 2011). Generally the rating aspect of recommender systems is more accurate using collaborative filtering techniques. However, if there is sparsity in the data available for collaborative filtering to be performed it could be combined with another technique (Adomavicius & Tuzhilin, 2008).

Context Awareness

"Context is any information that can be used to characterise the situation of an entity. An entity is a persona, place, or object that is considered relevant to the interaction between a user and an application" (Dey & Abowd, 2000). Abowd et al. (Abowd, et al., 1999) describes context-awareness as the use of context to provide task-relevant information/services to the user. Mark Weiser (Weiser, 1993) introduced the concept of 'Ubiquitous Computing' in the early 90s, since then there has been a great deal of research in the area of context awareness. However, this research has not resulted in a widespread adoption of all available types of context in mobile applications. It is important to use as many contextual conditions as possible to improve the validity of the information or services that the application is offering the user (Abbaspour & Samadzadegan, 2008). The various types of contextual conditions that will be discussed in this section are location, weather, time, social media sentiment and user preferences.

The three main location sensing techniques used outdoors are Global Positioning System (GPS), Global System for Mobile Communications (GSM) and WiFi. These methods use triangulation and proximity to determine a location. There are varying degrees of accuracy with these technologies

(Zhou, et al., 2010). Mobile devices use a combination of these techniques in the form of Assisted GPS (A-GPS). A-GPS will provide an approximate location at all times and often be more efficient than using standard GPS. Location with regard to tourism will be very important to the user as they would typically like to know what tourist attractions are near their current location. Knowledge of location is also important as the user will want information about the point of interest they are currently visiting and directions to this attraction (Teevan, et al., 2011).

Time can supply an additional level of intelligence that allows the application to determine if a point of interest is open before suggesting it to the user (Baltrunas & Amatriain, 2009). It is also possible to calculate the amount of time that a user stays at each attraction. This can be determined by checking if a user remains inside a defined geofence and then calculating the timespan of the length of stay (Fischer, 2012). The time related data could in turn be used to determine their level of interest in that particular attraction. It can be inferred that if a tourist stays at an attraction for a length of time greater than the average, they are more interested in that attraction. Time has been used as a context in the GUIDE application (Cheverst, et al., 2000) to provide information on whether an attraction is open or closed.

In the complex decision making performed by a tourist when deciding on a tourist attraction to visit, weather can often play an important role (Braunhofer, et al., 2014). A textual representation of the current weather conditions can be downloaded from an online web service. The possible weather conditions can be categorised as; good, neutral or bad. If the prevailing conditions are bad then indoor attractions will be given higher priority in the recommendation process. This change in recommendation is largely due to the impact that weather has on a tourist's planning decisions (Pearce, 2011). In addition to the mode of transport that the tourist has available, the distance that a tourist is prepared to travel is also dependant on the prevailing conditions.

In the past few years social media has become increasingly popular as a 'Micro Blogging' tool, especially with the introduction of Twitter. It is estimated that 65% of internet users maintain a profile on a social media network (Vitak, et al., 2012). Vitak (2012) outlines that Facebook is currently boasting user levels of greater than 800 million people worldwide. Millions of users are sharing their personal opinions on different aspects of life and this has provided a rich data source/corpus for opinion mining and Sentiment Analysis. Sentiment Analysis is a task that aims to identify sentiment expressions and determine the polarity (or valence) of the expressed sentiment (Davidov, et al., 2010). The aim is to determine if a selection of text contains positive, negative or neutral sentiment. Research in the area of Sentiment Analysis on a Micro-Blogging platform is at a very early stage in its development as Micro-Blogging is a relatively new development. However, Sentiment Analysis on large formal documents is not a new research area (Chen & Zhao, 2012). Sentiment Analysis can be performed on Micro-Blogs (tweets) in real time to determine the current "mood" of each tourist attraction. Using this data is important as tourism content created by tourists (from peers) is more reliable than content created by tourist information organisations. It can also be assumed that these messages have more support if they are forwarded to other users (in Twitter this is known as a retweet).

The tourists themselves and their preferences make a major contribution to their current context. Effective personalisation will ensure that suggestions made by a recommender system are more relevant to the current user (Buriano, 2006). However, it is also important when generating personalisation data implicitly that the user remains in control. This can be facilitated by allowing the user to explicitly change any incorrect assumptions made for personalisation purposes (Schmidt-Belz, et al., 2002). The main types of data that can be used to describe a person are age, gender, relationship status and number of children (Tang, et al., 2011). This data can be used as a starting point for the application when it is first launched with no related previous history. Data such as the user's age, relationship status and number of children can be combined to form a family cycle status for the tourist (Moutinho, 2011). The way in which a tourist explores a destination is highly dependent on their stage in the family cycle.

Implementation

VISIT (Virtual Intelligent System for Informing Tourists) is the mobile application that has been developed as part of this research. This application will allow users to see a list of available tourist attractions for the city they are currently visiting. This list is stored in an extensible structure, therefore, it can be updated at any time. The updated tourist attractions list will be pushed to the mobile device immediately similar to other internet based tour guides (Kenteris, et al., 2007). The recommendation provided in this application will take the form of a list of tourist attractions ranked in order of suitability. Different context types are used to provide a more accurate result in the process of personalisation. A probability value will be associated for every corresponding context type. These will then be aggregated to determine the probability of visiting each point of interest. Each of the probability values are combined with different weightings depending on the user's preferences. The resulting values will be ranked from most probable to least probable. This mobile application makes use of divergent context types such as location, time, weather, social media sentiment and user profile to make a recommendation.

The location of the device will be discovered using A-GPS to determine the distance between the user and each point of interest and allow the user to see their location on a map and get directions. However, distance is also used to determine the probability of a user visiting an attraction during the recommendation process. This is represented in an interconnected network of nodes with the nodes representing each of the points of interest and unidirectional links represent the probability of travelling between these nodes (see Figure 1). This is an important consideration, as the probability may be highly influenced by travel infrastructure between any two points. However, marketing incentives can also be an influencing factor regarding this decision. In order to determine if a user is within a specific point of interest, a geo-fence is defined around each of the tourist attractions. The reason for implementing this is due to the difficulty of determining the size of each of the different tourist attractions. A geo-fence is made up of 3 or more points that are linked together with a polygonal chain (see Figure 2). The chains with the most points are generally the most accurate, especially for larger or abnormally shaped tourist attractions.

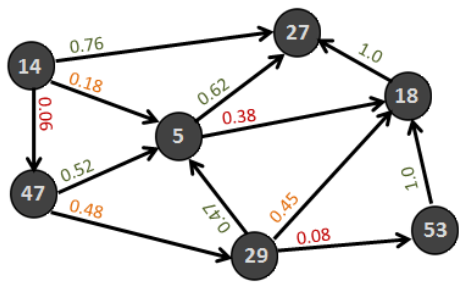

Figure 1 - Probability of travelling between nodes in an interconnected network.

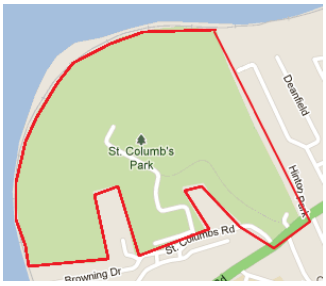

Figure 2 - : Geo-fences made up of 14/15 co-ordinates and a connecting polygonal chain.

Time can supply an additional level of intelligence which will allow the application to determine if a point of interest is open before suggesting it to the user. It is also possible to calculate the amount of time that a user stays at each attraction by checking if a user remains inside a defined geofence and calculating the timespan of the length of stay. This data could be compared against the average length of stay for each attraction which can be used to infer their level of interest in that particular attraction.

Current weather conditions can be downloaded from an online web service such as WorldWeatherOnline. There are multiple possible weather conditions and each of these are categorised as; good (1), neutral (0.5) or bad (0). If the prevailing conditions are bad then indoor attractions will be given higher priority in the recommendation process. This change in recommendation is largely due to the impact that the weather has on a tourists' planning decisions.

The user will have the ability to view real-time Social Media messages for each point of interest. Sentiment Analysis will be performed on Twitter messages in real time to determine the current "mood" of each tourist attraction. The Sentiment Analysis is performed using the Alchemy API (AlchemyAPI, 2012). In this study the researchers manually tested this tool on a corpus of 5370 tweets (one calendar month of data) and this test found that 86.01% of the tweets to be classified correctly. Once the analysis is performed, the result will be a sum total of positive, negative and neutral tweets matching the attraction keyword. The mood of the attraction can be inferred from the percentage of positive tweets set against the percentage of negative tweets. These messages are then displayed on the screen and colour coded (red for negative, green for positive and white for neutral).

One of the main contributors in using context to aid recommendation is the user's behaviour and preferences. Once the user's family cycle status is determined their preferences will be initially set to the average preferences for their demographic. These averages are initially determined using results gathered by the researchers from 148 questionnaires where tourists from each family cycle status were asked their preferences. These average preferences will be updated with continued application usage as their behaviour is learned. Furthermore, the "averages" held on the server for each family cycle status will be automatically updated with any implicit changes to the preferences for each user. The final form of user profiling is implicitly learning the user's behaviour based on their interaction with the application. This can be something as simple as checking how many times a user selects a particular attraction, how long they spend researching this attraction or if they follow through to visit the attraction.

User Study

Anonymous data was obtained from 40 participants who completed a user study followed by a questionnaire. The majority of these participants were staff or students at the University, most within the Computing Department. Some of the students were local students and some international students also took part in the study. Each person was asked to complete the user study that firstly required them to input their demographic information. The participants were then asked to rank their preferences for each type of tourist attraction (in the form of an ordered list where they could move these preferences up and down). They also ranked the types of contexts in order of importance (location, time, weather, social media sentiment and user preferences) using a dynamic ordered list. Once this was completed the user was presented with three tourist attractions. These tourist attractions are presented in a random order. One of these attractions was based on the recommendation of the VISIT system using all types of context. The second of these attractions was based on location (the closest attraction to the simulated location). The final attraction is a random attraction from the extensive list held within the application. The user was asked to envisage that they were in the situation described and at the location displayed. (A map was available for participants that were not familiar with the area.) The participants were then asked to choose which recommendation would be most appropriate for them. Once they selected the recommendation the page would reload with different randomly generated contextual conditions and three new recommendations. Each participant is then asked to make a selection for 10 different contextual combinations.

The Hawthorne effect (Adair, 1984) was also considered as it has the potential of leading to false results for the user study. This effect relates to evidence suggesting that people display behaviour changes when they feel that they are being observed. Therefore, it is important to ensure that this study was as unobtrusive as possible. In order to achieve this the participant was made aware that they will be assigned an ID number at random and it would not be possible to determine what they had selected. It was also important to keep a physical distance from the user when they are completing the study.

Once the user had completed the user study a questionnaire was automatically displayed. The questionnaire asked the participant 13 questions (of a qualitative and quantitative nature). The questionnaire aimed to determine the user's attitude towards technology, mobile technology and its use in tourism. It also asked questions relating to potential barriers and the impact of mobile technology on tourism. Finally, the questionnaire used a 7 point Likert scale to determine the impact location, weather, time, social media sentiment and user preferences would have on their decision when visiting tourist attractions.

Results

Table 1 and 2 provides an overview of demographic information (age, gender, marital status and children) for the sample size of 40 participants.

Marital Status		Age Group	
Single	47.5%	18-29	55%
Married	42.5%	30-39	22.5%
Engaged	5%	40-49	7.5%
Divorced	2.5%	50-64	10%
Other	2.5%	65+	5%

Table 1: Marital Status & Age Group

Gender	
Female	53%
Male	47%

Children	
Yes	42%
No	58%

Table 2: Gender & Children

One of the first aspects to note in analysis of results is the statistical significance between each of the presented age groups. The statistical data suggested that the null hypotheses would be accepted, therefore a Chi Square test was performed to determine statistical significance and frequencies between groups. The frequency table is presented in Table A1 and the Chi Square analysis is presented in Table A2. A statistical significance of .845 was observed during the analysis of context based recommendations selected. Before starting the study the significance level was set at 0.05 as this is the standard significance level for analysis in this field. This result means that each age group needs to be analysed and tested against the hypotheses independently.

Context Based Recommendation	
Age Group	**Frequency**
18-29	141
30-39	56
40-49	18
50-64	27
65+	14
Total	**256**

Table 3: Context Based Frequencies (Derived from Appendix Table A1)

A Chi Square test was performed to determine the statistical significance between the age groups of participants that selected Location Based Recommendations. Table A4 shows a statistical significance of 0.868. This statistical significance level is above the study significance level of 0.05, therefore each age group in this table should be tested against the hypotheses individually.

Location Based Recommendation	
Age Group	**Frequency**
18-29	44
30-39	16
40-49	7
50-64	4
65+	4
Total	**75**

Table 4: Location Based Frequencies (Derived from Appendix Table A3)

A further Chi Square test was completed to define the statistical significance between the age groups of participants that selected a Random Based Recommendation. An observed statistical significance of 0.372 is shown in Table A6. This significance level is not as high as the context based or location based recommendations. However, this value is higher than the study significance level of 0.05. Therefore, as a result each age group in this table should be tested against the hypotheses individually.

Random Recommendation	
Age Group	**Frequency**
18-29	35
30-39	18
40-49	5
50-64	9
65+	2
Total	**69**

Table 5: Random Based Frequencies (Derived from Appendix Table A5)

Discussion

The first significant result that can be observed is the difference between the selections of each age group. The five age groups represented in the study have provided different results in terms of the level at which they preferred each recommendation type. For example 70% of the 65+ age group preferred the context based recommendation. This may be due to the small sample size of participants that took part in the study from this group. However, the 40-49 age group least preferred the context based recommendation and this still resulted in 60% of their recommendation choices. It is interesting to see that some of the age groups (30-39 and 50-64) actually preferred the randomly generated tourist attraction over the closest attraction in terms of location.

Table 6 is presented showing the total percentage of participants at each age group that selected context based, location based and random recommendations. The main reason for showing the percentage values over the frequency data was to look at the group on the whole and analyse their behaviour. It is also possible to compare each of the groups to the mean in order to determine how close each age group is to the average selections. It is clear to see that the context based selections had been selected in the highest percentage over all age groups. Therefore, the alternative hypothesis has been accepted that Contextual Factors such as Time, Weather, Social Media Sentiment and User Preferences do have an impact on the decision of a tourist when visiting tourist attractions.

Total Recommendation Selections				
Age Group	**Context**	**Location**	**Random**	**N**
18-29	64.09%	20%	15.91%	220
30-39	62.22%	17.78%	20%	90
40-49	60%	23.33%	16.67%	30
50-64	67.5%	10%	22.5%	40
65+	70%	20%	10%	20
Mean	**64.76%**	**18.22%**	**17.02%**	**400**

Table 6: Total Recommendation Selections (Percentages)

Hypothesis: Contextual Factors such as Time, Weather, Social Media Sentiment and User Preferences do not impact the decision of a tourist when visiting tourist attractions.

Alternative Hypothesis: Contextual Factors such as Time, Weather, Social Media Sentiment and User Preferences do have an impact on the decision of a tourist when visiting tourist attractions.

Conclusion

This paper discusses VISIT, a novel context based mobile recommendation system for tourism. The main aim of VISIT is to provide an intelligent recommendation based on real-world environmental, temporal and personal context data. The first section introduced the research area, discussed the impact of mobile technology in tourism and outlined the proposed contribution of this research. The different types of mobile recommender systems were outlined in the next section in the form of content based recommender, collaborative filtering, knowledge based and hybrid recommender systems. The core objective of this system was to provide intelligent decision making that considers various types of environmental, personal and temporal contexts in the formation of a recommendation for tourists.

Theoretical Contribution

The main goal of this research was to create a tour guide system that provided an intelligent recommendation to the user, based on their current contextual conditions. In order to achieve this goal three distinct novel features were developed. The first of these features is the utilisation of five different context types to inform a recommendation within an intelligent tour guide system. The context types were both temporal, environmental and personal in nature. The contextual conditions represented within the application were Time, Location, Weather, Social Media Sentiment and User Preferences. Some of these contextual conditions have been used in differing combination in other tour guide systems. However, generally in previous systems there is an over-reliance on using Location alone as a context for providing meaningful recommendations. A significant aspect of this research is the amalgamation of five different contextual conditions. Social Media integration is highly significant as it has previously not been used to form a recommendation in a tour guide system.

Limitations

In the User Study it was deemed that 40 participants was a satisfactory sample size for evaluating the proposed hypotheses. However, once these participants were split into groups due to the statistical significance it was clear that some groups were over-represented and others were under-represented. For example, the number of participants in the 18-29 age group amounts to over half the participants that had taken part in the study. This has resulted in statistical methods being employed to ensure that sample size had no bearing on the outcome of the results. An example of this is using the Kruskal-Wallis test to independently analyse each of the groups.

In order to effectively determine the success of the recommender system, various combinations of contextual conditions were simulated. Simulating contexts provided the ability to randomly assign different contextual conditions to ensure an effective recommendation under all circumstances. However this is not a complete reflection of the 'real world' because in a 'real world' field study the majority of the contextual conditions will be similar. For example, if a tourist visited numerous attractions in one day, then it is likely that the weather conditions would be the same for the majority of the day, especially in the summer season. So it should be kept in mind that although the simulated data covers all possibilities it does not reflect real life actuality.

Practical Contribution

The purpose of this research was to provide an intelligent recommendation based on real-world environmental, temporal and personal context data. The VISIT application was developed in order to encompass the aims of this project in the form of a mobile application for tourism. A user study took place in order to evaluate the VISIT application and test the two hypotheses outlined in this paper. This research presented results that supported the alternative hypothesis 'Contextual Factors such as Time, Weather, Social Media Sentiment and User Preferences do have an impact on the decision of a tourist when visiting tourist attractions'. This is shown both in the recommendation selections (from the user study) and the questionnaire data (from the pre-experiment questionnaire). It can therefore be concluded that the VISIT system with its multi-contextual approach to decision making does provide more intelligent recommendations than systems that rely on location based recommendations.

APPENDIX A – USER STUDY RESULTS

Age Group * Total Context Crosstabulation

Count

		Total Context								
		3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	Total
Age Group	1	1	1	3	8	4	3	1	1	22
	2	0	2	3	0	0	3	1	0	9
	3	0	1	0	1	0	1	0	0	3
	4	0	1	0	0	1	2	0	0	4
	5	0	0	0	1	0	1	0	0	2
Total		1	5	6	10	5	10	2	1	40

Table A1: Total Frequency of Context Recommendation Selections (Age Groups)

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	20.505[a]	28	.845
Likelihood Ratio	26.807	28	.529
Linear-by-Linear Association	.155	1	.694
N of Valid Cases	40		

a. 38 cells (95.0%) have expected count less than 5. The minimum expected count is .05.

Table A2: Context Recommendation Selections Age Group (Chi-Square)

Age Group * Total Location Crosstabulation

Count

		Total Location						Total
		.00	1.00	2.00	3.00	4.00	5.00	
Age Group	1	5	3	6	4	3	1	22
	2	1	3	3	1	1	0	9
	3	0	0	2	1	0	0	3
	4	1	2	1	0	0	0	4
	5	0	0	2	0	0	0	2
Total		7	8	14	6	4	1	40

Table A3: Total Frequency of Location Recommendation Selections (Age Groups)

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	13.205[a]	20	.868
Likelihood Ratio	15.471	20	.749
Linear-by-Linear Association	.585	1	.444
N of Valid Cases	40		

a. 29 cells (96.7%) have expected count less than 5. The minimum expected count is .05.

Table A4: Location Recommendation Selections Age Group (Chi-Square)

Age Group * Total Random Crosstabulation

Count

		Total Random						Total
		.00	1.00	2.00	3.00	4.00	5.00	
Age Group	1	4	7	8	0	3	0	22
	2	2	3	0	2	1	1	9
	3	1	0	1	1	0	0	3
	4	0	2	1	0	0	1	4
	5	1	0	1	0	0	0	2
Total		8	12	11	3	4	2	40

Table A5: Total Frequency of Random Recommendation Selections (Age Groups)

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	21.429[a]	20	.372
Likelihood Ratio	26.088	20	.163
Linear-by-Linear Association	.059	1	.808
N of Valid Cases	40		

a. 28 cells (93.3%) have expected count less than 5. The minimum expected count is .10.

Table A6: Random Recommendation Selections Age Group (Chi-Square)

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