Designing Information for Artificial Intelligence: Path Recommendation and User Acceptance in a Virtual Space

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Abstract

In this study, the authors propose two information layout strategies (informative layout and decisive layout) that influence the user acceptance rate on recommended information. The informative layout is the degree of descriptions in the recommendation process. The decisive layout is the degree of choices in recommendations. Thus, the objective of the paper is to discover how users' acceptance of a recommendation changes when the recommendation is displayed in different degrees of informative and decisive layouts. To this end, we have conducted the following tasks: 1) Sophisticated software was created with Javascript to conduct experiments with users online; 2) Experiment subjects (N=247) with various education and demographic levels were recruited; 3) User acceptance rate depending on the information layout strategy was collected; 4) The relationships between information layout strategy and user acceptance of the recommended information were computationally analyzed. The results of the study indicate that the information layout strategy proposed in this research significantly influences user acceptance of the recommended information. Also, this research identified effective combinations of informative and decisive layouts to maximize the user acceptance.

Keywords: Information Layout, Artificial Intelligence, User Acceptance, Virtual Space, Computational Design.

Introduction

Both design academics and professionals have widely investigated the relationships between artificial intelligence (AI) and design. In academia, research has been focused on making the design process more innovative and effective by implementing artificial intelligence in design (Tang et al., 2013; Rodgers et al., 1998; Berger, 1980; Reich et al., 1993). In practice, by collecting, analyzing, and implementing the findings on user behavior, the data-driven nature of artificial intelligence has improved the user experience. One of the most widely known examples is Apple's iOS keypad. The iOS keypads provide informative recommendations to the users. For instance, when the user inputs the text "sch," the system automatically asks if the user intended to type the word "school." Furthermore, the system can minimize typos by learning the user's typing pattern and modifying the range of the input area. Artificial intelligence thus ultimately provides optimized experiences by understanding user needs and wants through determination of user behavior. Global companies such as Samsung started incorporating artificial intelligence into their software solutions to maximize the efficiency and usability for users (Bradshaw, 2017). Watson, for example, studied over 605,000 medical records in 2 million pages of text and it is already better at diagnosing lung cancer than human doctors (Friedman, 2014). Another trend of artificial intelligence in design is conversational user interfaces such as Chabot and voice recognition. Alexa developed by Amazon uses conversational user experience to communicate with the users and studies their buying patterns to suggest new products to sell (Nunes, 2015). It is clear that artificial intelligence has the ability to come up with informative recommendations to users by continuously studying those users. In this respect, the implementation of artificial intelligence in design can change the conventional process of design both academically and professionally. However, the relationship between the ability to produce recommendations through highly accurate predictions and users' acceptance of the recommendation is an important issue that needs to be addressed. More specifically, will users accept the recommendation from a computer? If they do, why would they trust and take the suggestions? Lee and See (2004) defined trust as the cognitive process towards an agent that helps to achieve one's objective in uncertain and vulnerable situations. Regardless of whether the artificial intelligence suggests optimized information, if the users have no relationships with the system, they will likely not trust the information. According to Chau et al. (2000), information has different acceptability to users depending on how it is presented. Designers have the greatest freedom to manipulate how information is displayed. They decide the relevance and significance of the information and structure the information accordingly (Wurman, 1996). By identifying and implementing the effect of information layout, the output from the recommended information can be more acceptable to the users.

In this research, we propose two information layout strategies that influence user acceptance of recommended information: 1) informative layout and 2) decisive layout. Informative layout is the degree of description in the recommendation process. Decisive layout is the number of choices in recommendations. In this study the authors focus on identifying the relationships between information layout strategy and users' acceptance of recommended information. Thus, the objective of the paper is to discover how users' acceptance of information changes when the information is displayed in different degrees of informative and decisive layouts. To this end, we have conducted the following tasks: 1) Sophisticated software was created to conduct experiments with users online; 2) Experiment subjects with various education and demographic levels were recruited; 3) user acceptance of information depending on the information layout strategy was collected; and 4) The relationships between information layout strategy and user acceptance of recommended information was analyzed.

Related Works

Automated Information and Trust

Artificial intelligence is everywhere. It is in driving, manufacturing, information retrieval, and even security. Automation offers the potential to collect big data, learn unseen patterns, and provide meaningful information. However, accidents and tragedies related to or caused by automated processes have adversely affected the public's perception of automation and artificial intelligence. For example, Tesla's automated driving car crashed and killed the passenger due to its failure to detect a truck against the bright sky (Boudette, 2017). According to Parasuraman and Riley (1997), people relate such negative responses to misuse and disuse of automation. Understanding the cause of how people disuse and misuse the automation is the key to identifying how people reject automation capabilities (Lee and See, 2004). One of the critical elements of information acceptance is trust (Staab et al., 2008). Interestingly, humans show similar human-to-human interaction patterns when they respond to technology (Reeves and Nass, 1996). Trust is a social and psychological concept, but it is an essential element to understanding better human-automation partnerships (Lee and See, 2004). For instance, Lee and See (2004) identified three bases of trust: 1) performance; 2) process; and 3) purpose. The performance shows the historical performance of the automation. Therefore, it is important to show previous results to build trust. The process defines how the automation works. Users tend to trust automation more when they understand how it works. The purpose refers to why the automation was developed. In this case, the operator will trust the automation to achieve the objective. Constant communication of what automation does and how it can benefit the user is an essential element (Lieberman, 2009). Lieberman (2009) argued that artificial intelligence needs to have more tutorials or presentations of its features to introduce its capabilities to users better. The way the information is displayed is one of the essential qualities of trust (Lee and See, 2004). According to Cyr (2008), information design has significant relationships to trust. In other words, depending on how we structure the way information is displayed, people's trust in the information can vary.

Information Architecture Design

Information Architecture Design is a process that forms and organizes information to provide meaningful insights. Rich and diverse information is useless to the user when not presented in the right way (Kim, 2005). For instance, data can serve as useful elements to extract hidden insights that were not known before because the display of data significantly influences clarity and excellence of thoughts and objectives (Tufte, 1997). However, data alone is not enough for users or customers. It is the designer's job to make sense of the data and translate it to useful information to users (Cyr, 2008; Shedroff, 1999). For designers, it is critical to understand what information is relevant to users since the manner in which information is presented influences users' acceptance (Chau et al., 2000). Therefore, restructuring and reorganizing the design layout of information is a critical task conducted by information designers. Horn (1999) described the objectives of information design as follows: "1. to develop documents that are comprehensible, rapidly and accurately retrievable, and easy to translate into effective action; and 2. to design interactions with equipment that are easy, natural and as pleasant as possible." These objectives suggest that the goal of information design is more efficient and effective communication. By doing so, information design solved many problems in the design of human-computer interfaces including airplane cockpits (Vicente, 2004) and nuclear power plants (Norman, 2013). Thus, the goal of information design is to make information clearer for users (Wurman, 1996). Designers, therefore, try to create diverse information design layouts so users can better understand and accept the information.

Information Layout Strategy in User Experience

Information design influences the clarity and user acceptance of recommended information. However, the current literature on information layout cannot explain what types of information layout influence user acceptance of recommended information. Thus, we propose two information layout types to identify the relationships between user acceptance and recommended information: informative layout and decisive layout. The definition of the informative layout is the degree of description in the recommendation process. For example, a high informative layout would show information such as estimated arrival time along with the calculation process including gasoline usage, traffic, wind speed, and historic pattern values. On the other hand, a low informative layout would show the estimated arrival time only. Unlike informative layout, the definition of the decisive layout is the number of choices in recommendations. A high decisive layout would show a single most optimized recommendation to the userA The low decisive layout would show possible recommendations. A mixture of both informative and decisive layout is used in the real- life design cases. Apple-IBM's flight solution is a good example of high informative and high decisive layouts. Apple-IBM created a solution that organizes a pilot's task before-during-after flight. The solution identifies the most important and critical variables (gasoline, taxi duration, weather) to recommend alternative airports in case of an emergency. As shown in Figure 1-a, it suggests an alternative airport in high decisive recommendations with a high informative layout. Google Map navigation has high informative and low decisive layouts (Figure 1-b). Google Map is widely used all around the world to locate or navigate to a place. Google Map navigation shows the estimated time of the path and supporting information such as distance, traffic, and routes. It shows alternative recommendations simultaneously. Football Manager has low informative and high decisive layouts (Figure 1-c). Football Manager is a simulation game that a user plays as a football club coach. The system recommends a new player to recruit without descriptions. It is impossible to understand why the player was recommended, and the system also does not provide alternate recommendations. Interpark Tour is one of the most well known online travel agencies (Figure 1-d). Interpark Tour has low informative and low decisive layouts. Their numerous product recommendations are based on prices without calculation details such as the number of stops, durations, and baggage allowance. Based on the proposed informative and decisive layouts, this research focuses on identifying the relationships between how information is displayed and user's acceptance of recommended information.

	Low Decisive	High Decisive
Low Informative	 a)	 b)

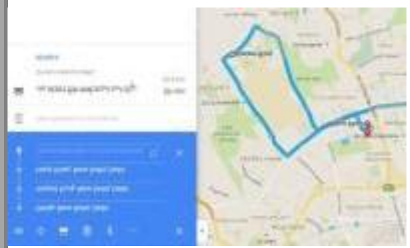
High Informative	 c)	 d)

Figure 1. Information Layout Strategy: a) Interpark Tour with low informative and high decisive layouts; b) Football Manager with low informative and high decisive layout; c) Google Map Navigation with high informative and low decisive; d) Apple-IBM flight planner with high informative and high decisive.

Methods

To test the relationships between information layout strategy and users' acceptance of recommended information, we conducted a series of experiments. First, we created software with Javascript to collect user acceptance of recommended information. Second, we created a virtual map to test user navigation patterns (Figure 2). Third, user interaction methods within the virtual map were created. Fourth, a series of experiments including tutorials were designed. Lastly, the collected data was computationally analyzed.

Figure 2. The Map for Programmed Path Recommendation System

Experimental Setting

Path Recommendation Software

The experiment platform was programmed with Javascript. The platform simulates the navigation system under uncertain locations. The navigation works in a turn based system where the user can move one cell at a time in eight different directions. The size of the map is 20 by 20 cells allowing rooms for generating alternate path recommendations. The concept of fog was used to visualize uncertainty. Once the off-road car moves a cell, the cells next to the car are discovered. Dijkstra’s Algorithm was used to recommend the most efficient path between node a and node b. It iteratively selects unvisited nodes and calculates the shortest distances to their neighbor (Skiena, 1999). The pseudocode for the algorithm used in this research is as follows:

```
function FindShortestPath(Source S, Destinaton D, Graph G)n{

  Initial Q                                   //Initial Set of Unvisited Node
  Visited S                                   //Visited Node Set
  for each Node V in Graph G{
    Distance[V] = Infinity                    //initially, distance from source to vertex V is set to infinite
    Previous[V] = Undefined                   //Previous node in shortest path to reach node V
  }
  Distance[S] = 0                             //Distance from Source to Source is 0
  Q.push(V)                                   //push all Node into unvisited set

  while Q.isNotEmpty{
    vertex U = Q.popMinimumDistance()     //pop a Node with minimum distance(in 1st loop, source is
    selected) if U == D{                      //If next node is destination, job is done
      Previous[V] = U
      return Distance, Previous
    }
    for each neighborNode V of U{             //Visit all neighbors of selected
      node alt = Distance[U] + Distance[from U to V] //edge relaxation
      if alt < Distance[V]{
        Distance[V] = alt
        Previous[V] = U
      }
    }
  }
  return Distance, Previous
}
```

The objective of this research is to understand how users’ acceptance of recommended paths differs according to the information layout strategy: 1) informative layout; 2) decisive layout. As shown in Figure 3, the informative layout is defined by the degree of description in the recommendations, and the decisive layout is defined by the number of choices in the recommendations. Thus, a detailed description of the recommendation process is shown in the high informative layout and a limited description is shown in the low informative layout. The most optimized recommendation was presented in the high decisive layout, and multiple recommendations were presented in the low decisive layout.

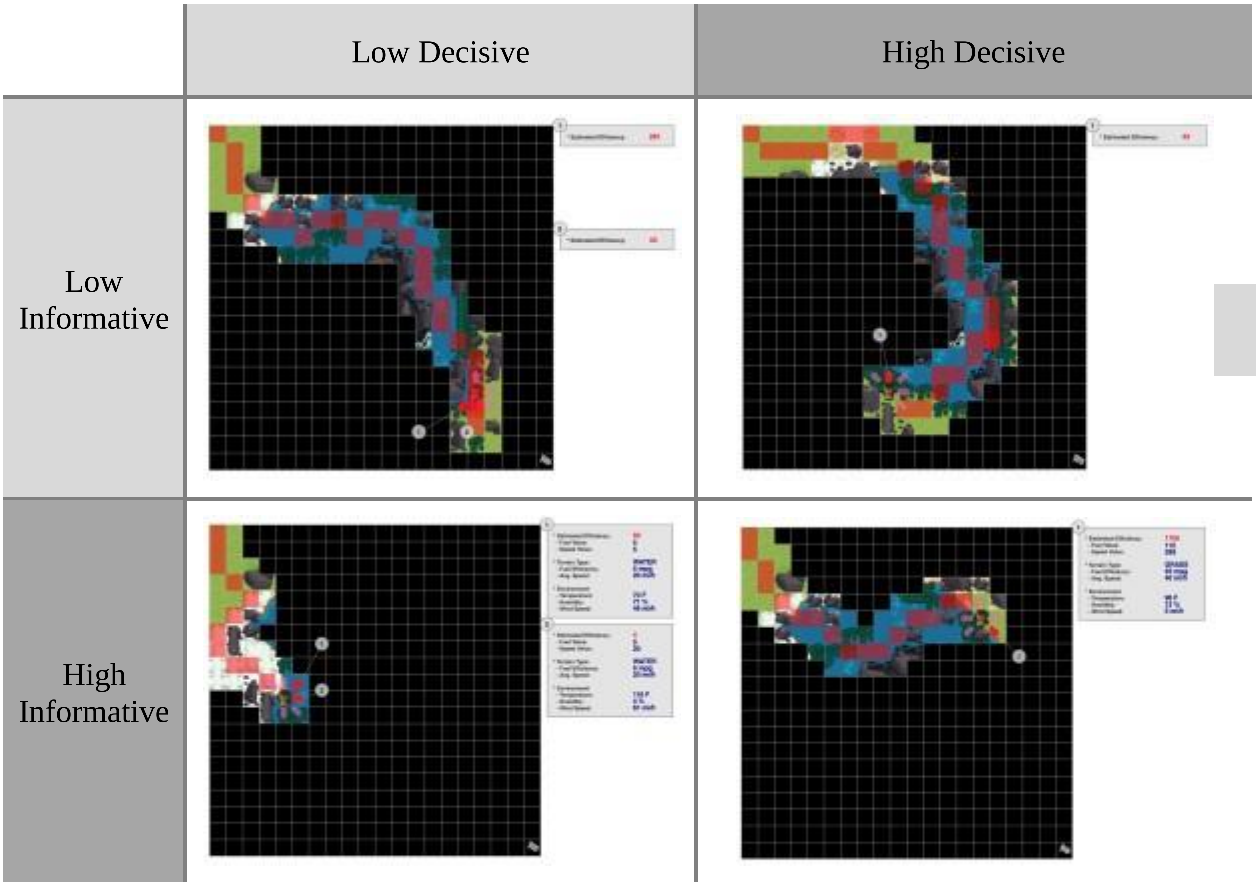


Figure 3. Informative and Decisive Information Layout Strategies

The geographical variables were implemented as weighting values in Dijkstra's algorithm. The fuel efficiency (F) and speed (S) were measured to calculate the efficiency of the path. The geographical variables are weather, temperature, and obstacle information (Figure 4). Also, there are different land types such as grass (F=45mpg, S=40mph), dunes (F=21mpg, S=30mph), swamp (F=28mpg, S=15mph), ice (F=11mpg, S=25mph), water (F=5mpg, S=20mph), and rock (impossible to pass) that adversely impact efficiency in navigation. For example, the moving cost is calculated by C = Global Variables * Texture on Land Type. The speed is calculated by T: Global Variables * Speed on Land Type. Therefore, both the algorithm and the human subjects need to carefully consider the geographical variables to identify the most efficient path to a target destination.

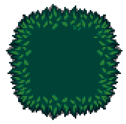
Terrain Type						Global Values		
Grass	Dessert	Snow	Swamp	Water	Rock	Humid.	Temp.	Wind
						%	°F	
45 mpg	21 mpg	28 mpg	11 mpg	5 mpg	0 mpg	random	random	random
40 mph	30 mph	15 mph	25 mph	20 mph	0 mpg	random	random	random

Figure 4. Fuel efficiency and speed difference according to terrain types and global values

Subjects

Experiment subjects were recruited from the Amazon Mechanical Turk. The subjects were United States residents (mean age = 34.834 minimum age = 19; maximum age = 76; median =32). 247 participants were selected for the experiment. There were 139 males and 108 females. The path recommendation software that we developed was linked to the Mechanical Turk so the subjects could participate in the experiment seamlessly. A 7-point Likert scale was used to ask about their “tolerance of artificial intelligence,” “frequent usage of artificial intelligence,” and “degree of understanding of artificial intelligence.” The subjects received payment for their participation, and additional “bonus” payments were given based on their performance.

Experiments

This research consisted of two experiments. The first part of the experiment was conducted on a self-programmed path recommendation system. Subjects were asked to navigate through the assigned destinations on the path recommendation platform that we programmed. To consecutively measure users’ acceptance of the recommendation system, users can move one cell per move. The size of the map is 20 by 20 cells, and the shortest path that a user can get to the destination requires 23 moves (Figure 5). The subjects were randomly assigned to four different groups, and each group was tested in a specific information layout setting: (1) informative low + decisive low; 2) informative low + decisive high; 3) informative high + decisive low; 4) informative high + decisive high). At every move, path recommendations were provided to the subjects according to the information layout strategy, as shown in Figure 3. The user acceptance rate was measured based on the rate of subjects taking the recommendations provided by the system. Before subjects navigated the virtual space, a full map of the space was displayed to the subjects for 0.5 seconds. The purpose of this is to put subjects in an uncertain and vulnerable situation.

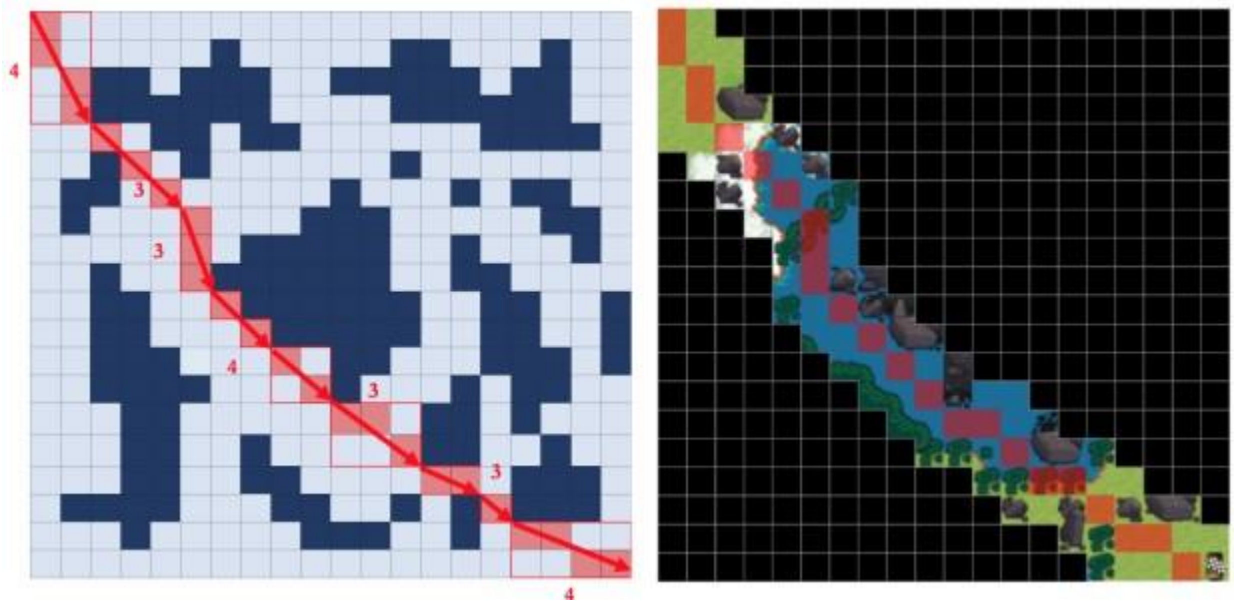


Figure 5. Shortest Path to the Target Destination

The second part of the experiment consists of survey questions in a 7 point Likert scale. The following are some of the questions in the survey: “How accurate do you think the Artificial Intelligence recommendation in this study are?”, “How useful do you think the Artificial Intelligence recommendation in this study is?”, “How reliable do you think the Artificial Intelligence recommendation in this study is?”, “How much are you interested in Artificial Intelligence in general?”, “How reliable is the Artificial Intelligence recommendation system in general?” The subjects then conducted demographic surveys.

Implementation and Results

The average number of moves the subject took to reach the target destination was 39.202 moves (average of 2.760 seconds per move). If the subjects took the most efficient path, they were able to get to the destination in 23 moves. Figure 6 shows the users’ acceptance of recommended information by information layout strategy.

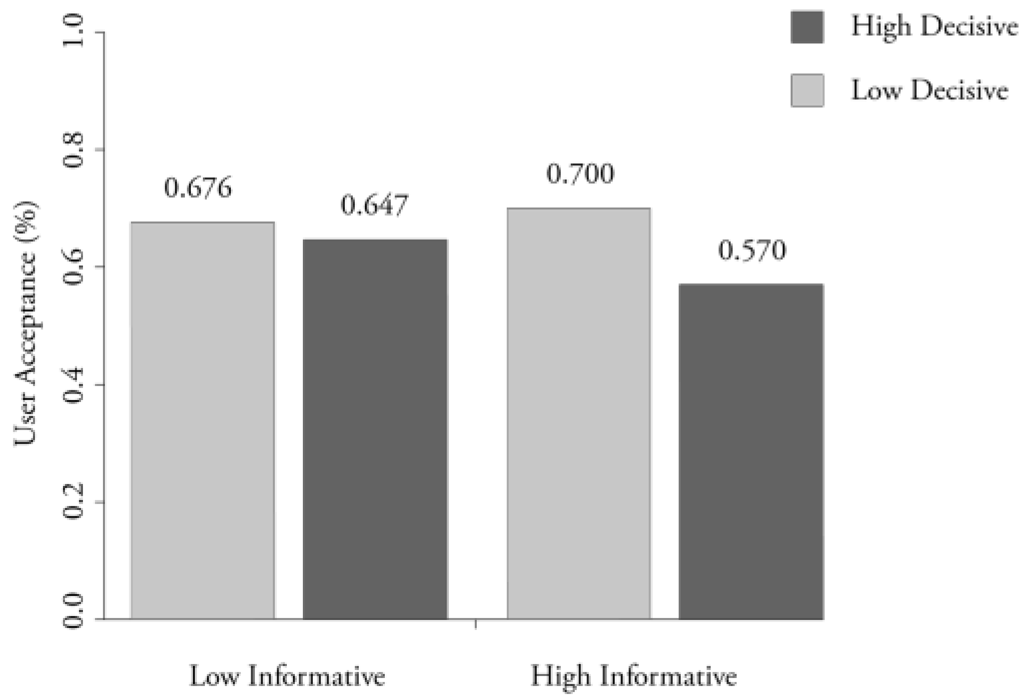


Figure 6. Informative and Decisive Information Layouts on User Acceptance Rate

To examine how differently people accept or reject recommendations depending on information layouts offered by an AI, we conducted a 2 (informative: high vs. low) x 2 (decisive: high vs. low) analysis of variance (ANOVA). The independent variables were informative layout and decisive layout, dependent variable was user acceptance rate, and an interaction of informative and decisive layout.

A significant main effect of decisive layout was found (F = 10.316; $p < 0.001$; participants accepted recommendations more when the recommendations were in low decisive layouts). This result is caused because simply more number of recommendations were suggested in low decisive layout condition. Whereas both high and low informative layout and a high decisive layout provide a single recommendation, a low decisive layout particularly provides multiple recommendations. Since the default possibilities of a low decisive layout are higher than other layouts, participants were more willing to accept the recommendations from a low decisive layout. More importantly, a significant interaction of informative and decisive layouts was found (F = 4.110; $p < 0.044$; table 1). To probe the interaction specifically, we conducted contrast analyses. In the low informative condition, both the low ($\beta = -0.234$, t(243) = -0.671, $p = 0.503$) and high ($\beta = 0.293$, t(243) = 0.815, $p = 0.416$) decisive layouts showed no significant difference with user acceptance. In contrast, users accepted less recommendations in the high decisive layout than the low decisive layout in high informative condition ($\beta =$ 0.130, t(243) = 3.815, $p < 0.000$). In addition, this result consistently confirms within high decisive layout conditions. In high decisive condition, users accepted less recommendations in high informative (vs. low informative) layout ($\beta = 0.077$, t(243) = 2.211, $p = 0.028$). The result of the study showed that the user acceptance of recommendation from AI is at its lowest when the recommendation layout is in both high informative and high decisive. We assume that these results – people tend to accept less recommendation when the recommendation is provided in both high informative and high decisive layouts – were driven by the free will of human beings. Belief in free will provides a feeling of stability and control, and humans have a strong preference for freely choosing (Wertenbroch et al., 2008). In addition to the human free will of choices, if the information of recommendations given by AIs is cognitively demanding to understand, people may resist advice from AIs even more. Similar to choice overload, information overload can lead to negative impact on decision making (Scheibehenne et al., 2010). Therefore, adding a cognitively-demanding aspect of high informative layouts to an absence of choice freedom of high decisive layouts should boost people's negative reactions toward recommendations, and in turn, decrease user acceptance rates. In sum, the results indicate that to increase the user acceptance of recommendations, AIs need to provide information that is easy to understand and provide more than one recommendations that users can decide in choosing the recommendations.

Table 1. ANOVA Results

Source	Type III Sum of Squares	df	Mean square	F	Significance
Informative	0.043	1	0.043	1.143	0.286
Decisive	0.387	1	0.387	10.316	0.001***
Informative * Decisive	0.154	1	0.154	4.110	0.044*

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Conclusion

In this research, the authors proposed a new information layout strategy, informative layout and decisive layout. We identified that the information layout strategy significantly influences user acceptance. Thus, depending on how designers structure the information layout, user acceptance of the recommended information can vary. Also, we identified the most effective combinations of informative and decisive layouts to maximize the user acceptance. However, we showed that the results obtained in this research might vary depending on the domain of application. As a result, we plan to research the proposed methods in different fields such as finance, medicine, and education to increase the applicability of the research. Another important area to investigate in the future is how user acceptance relates to information layout over time. Such investigation can reveal the mechanism underlying how users build trust over the recommended information.

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