Tampere University

AHMAD HASSAN AFRIDI

Supporting Serendipity through Interactive Recommender Systems in Higher Education

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Supporting Serendipity through Interactive Recommender Systems in Higher Education

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A Thesis Submitted for partial fulfillment of the degree of Doctor of Philosophy in Doctoral Programme of Humans and Technology, at Tampere University, Finland

DEDICATION

This doctoral thesis is dedicated to my Parents,

Engr. Hassan Javid Afridi & Mrs. Riffat Javid

and to my late son, Mahad Hassan Afridi

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ABSTRACT

Serendipity is defined as the surprising discovery of useful information or other valuable things. In recommender systems research, serendipity has become an essential experiential goal. However, relevant to Human-Computer Interaction, the question of how the user interfaces of recommender systems could facilitate serendipity has received little attention. This work investigates how recommender system-facilitated serendipity can be applied to research article recommendation processes in the context of higher education. In particular, this work investigates the use of recommender system applications in developing countries as most studies in developing countries have focused solely on implementation, rather than user experiences. This dissertation describes the design and development of several user interfaces for recommender systems in an attempt to improve our understanding of serendipity facilitation with the help of user interfaces. By studying these systems in a developing country, this dissertation contrasts the study of recommender systems in developed countries, examining the contextual and cultural challenges associated with the application of recommender systems.

This dissertation consists of five empirical user studies and a literature review article, contributing novel user interface designs, open-source software, and empirical analyses of user experiences related to recommender systems in a Pakistani higher education institution. The fortunate discoveries of recommendations are studied in the context of exploring research articles with the help of a recommender system. This dissertation covers both constructive and experimental research. The articles included in this dissertation present original research experimenting with different user interface designs in recommender systems facilitating serendipity, discuss stakeholder requirements, assess user experiences with recommended articles, and present a study on task load analysis of recommender systems. The key findings of this research are that serendipity of recommendations can be facilitated to users with the user interface. Recommender systems can become an instrumental technology in the higher education research and developing countries can benefit from recommender systems applications in higher education institutions.

TIIVISTELMÄ

Serendipiteetin käsite viittaa onnekkaisiin sattumuksiin, jossa hyödyllistä tietoa tai muita arvokkaita asioita löydetään yllättäen. Suosittelujärjestelmien tutkimuksessa serendipiteetistä on tullut keskeinen kokemuksellinen tavoite. Ihmisen ja tietokoneen vuorovaikutuksen kannalta olennainen kysymys siitä, kuinka käyttöliittymäsuunnittelu suosittelujärjestelmissä voisi tukea serendipiteetin kokemusta, on kuitenkin saanut vain vähän huomiota. Tässä työssä tutkitaan, kuinka suosittelijajärjestelmän mahdollistamaa serendipiteetin kokemusta voidaan soveltaa tutkimusartikkelien suositteluihin korkeakouluopetuksen kontekstissa. Erityisesti työ tarkastelee suositusjärjestelmäsovellusten käyttöä kehittyvissä maissa, sillä suurin osa kehittyvissä maissa tehdyistä tutkimuksista on keskittynyt pelkästään järjestelmien toteutukseen. Tässä väitöskirjassa kuvataan suosittelujärjestelmien käyttöliittymien suunnittelua ja kehittämistä, tavoitteena ymmärtää paremmin serendipiteetin kokemuksen tukemista käyttöliittymäratkaisuilla. Tutkimalla näitä järjestelmiä kehittyvässä maassa (Pakistan), tämä väitöskirja asettaa suosittelujärjestelmien käytön vastakkain aikaisempien teollisuusmaissa tehtyjen tutkimusten kanssa, ja siten mahdollistaa suositusjärjestelmien soveltamiseen liittyvien kontekstuaalisten ja kulttuuristen haasteiden tarkastelua.

Väitöskirja koostuu viidestä empiirisestä käyttäjätutkimuksesta ja kirjallisuuskatsausartikkelista, ja työ tarjoaa uusia käyttöliittymäideoita, avoimen lähdekoodin ohjelmistoratkaisuja sekä empiirisiä analyyseja suositusjärjestelmiin liittyvistä käyttäjäkokemuksista pakistanilaisessa korkeakoulussa. Onnekkaita löytöjä tarkastellaan liittyen tutkimusartikkelien löytämiseen suositusjärjestelmän avulla. Väitöstyö kattaa sekä konstruktiivista että kokeellista tutkimusta. Väitöskirjan artikkelit esittelevät alkuperäistä tutkimusta, jossa kokeillaan erilaisia käyttöliittymämalleja, pohditaan sidosryhmien vaatimuksia, arvioidaan käyttäjien kokemuksia suositelluista artikkeleista ja esitellään tutkimusta suositusjärjestelmien tehtäväkuormitusanalyysistä.

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ABBREVIATIONS

UI	User Interface
IT	Information Technology
CS	Computer Science
BS	Bachelor of Science
MS	Master of Science
BX	Bookcrossing
RAAS	Recommender-as-a-Service
PAAS	Platform-as-a-Service
IMS	Institute of Management Sciences
API	Application Programming Interface
Top-N List	Top Ranked Items list
ICT	Information Communications Technology

ORIGINAL PUBLICATIONS

Publication I	Afridi, A. H. (2019). Serendipitous Recommenders for Teachers in Higher Education. In Handbook of Research on Faculty Development for Digital Teaching and Learning (pp. 333-353). IGI Global.
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Publication VI	Afridi, A. H., & Outay, F. (2021). Triggers And Connection-Making for Serendipity Via User Interface in Recommender Systems. Personal And Ubiquitous Computing, 25(1), 77-92. Springer
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Authors' Contributions in Publications

Publication. No.	**Authors and Contribution**
Publication I	Mr. Ahmad Hassan Afridi, 100 % contribution
Publication II	Mr. Ahmad Hassan Afridi, 100 % contribution
Publication III	1. Mr. Ahmad Hassan Afridi = 80% (Paper writing, research design, conducting experiments, performing analyses) 2. Dr. Ansar ul Haq Yassar and Dr. Elhadi M. Shakshuki =20 % (Paper composition, miscellaneous issues, and publication)
Publication IV	1. Mr. Ahmad Hassan Afridi = 80% (Paper writing, research design, conducting experiments, performing analyses) 2. Dr. Fatma Outay =20 % (Paper composition, miscellaneous issues, and publication)
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1 INTRODUCTION

This chapter introduces the motivation and research problems addressed in this doctoral dissertation. The research questions and the key concepts of serendipity and recommender systems are described. Finally, this chapter outlines the research contributions and structure of this dissertation.

1.1 Serendipity in Recommender Systems

Serendipity is defined as "the faculty of making fortunate discoveries by accident" (Andel, 1994) and tends to focus on the outcome of accidental discoveries. When discussing the facilitation of serendipity via recommender systems, the outcome of such encounters is difficult to measure as outcomes may manifest days, months, or even years following the encounter. Thus, for this thesis, I define serendipity as a surprising encounter that has the potential to yield positive outcomes (Figure 1). Serendipity has significantly impacted scientific discoveries and inventions (Ramsay, 1990). The history of science and technology is full of serendipitous discoveries. From drug discovery (Ban, 2006) to chemistry (Rulev, 2017) and material sciences (Magennis *et al.,* 2016), the accidental discovery of research outcomes has demonstrated the relevance of serendipity as a phenomenon.

Figure 1 represents the definition of serendipity that is used in this thesis and provides a perspective of how I view serendipity when developing user interface designs to facilitate serendipity in recommender systems. The relevancy of the recommendations provided by the recommender system is defined by the outer circle; each recommendation is represented by a small blue or maroon circle inside the relevancy boundary. Note that serendipitous recommendations (shown in maroon) lie at the periphery of the relevancy circle, indicating that these recommendations are near accurate (lie inside the relevancy circle) but may be more unexpected or novel than recommendations found near the center.

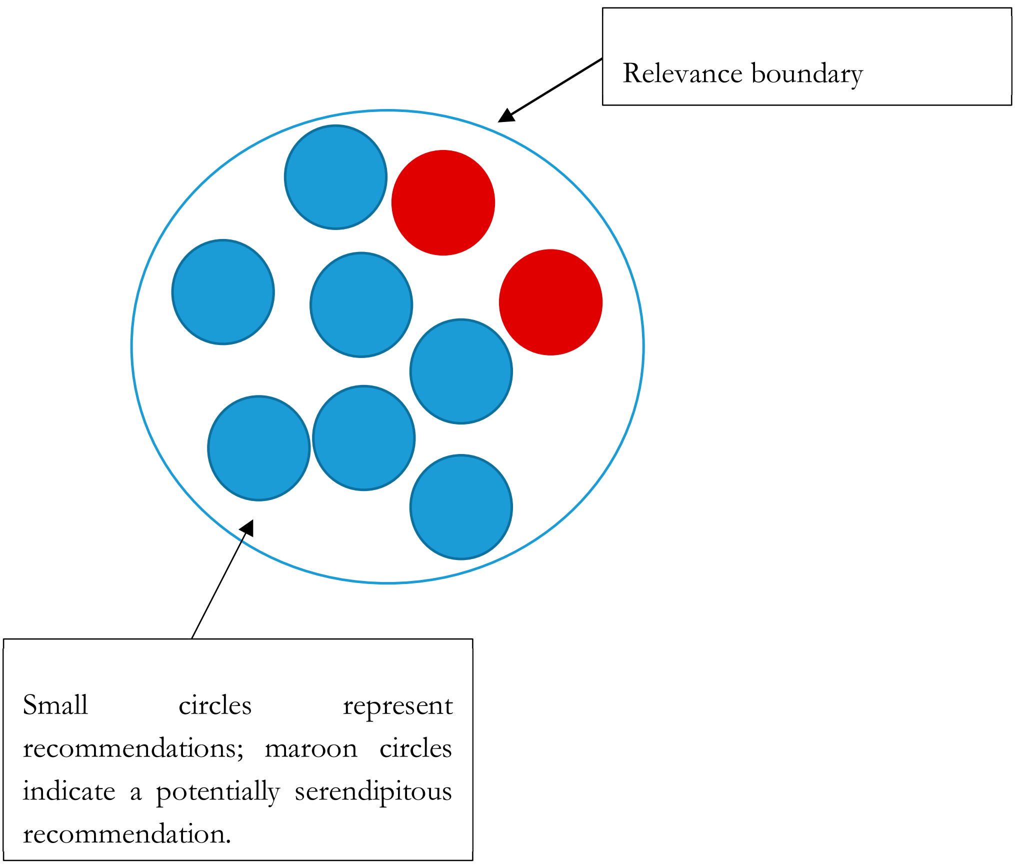

Figure 1. Definition Of Serendipity Utilized in this Thesis

In a modern technologized world, serendipity is worth the investment of research effort. Much of the recent information system, specifically recommender systems, research has focused on facilitating serendipity at the user's end via algorithmic advancements (Kotkov, Wang, & Veijalainen, 2016). To harness this potential, recommender systems must-have features to support serendipity, that is *serendipity facilitation mechanisms*. Serendipity facilitation has been investigated and has many advocates (McBirnie, Ford, McCay-Peet, & Makri, 2016). Serendipity is pursued in various information systems, specifically recommender systems, to help solve problems such as presenting novel products to users, resolving filter bubbles, or addressing echo chamber problems introduced by search engines (Fletcher & Nielsen, 2018). Artificial serendipity is defined as serendipity that is "facilitated or triggered with the help of artificial agents such as information communication technology (ICT) applications" (Olshannikova, Olsson, Huhtamäki, Paasovaara, & Kärkkäinen, 2020).

Interactive recommender systems are a class of recommender systems that incorporate user controls and visualization techniques to interact with users. In this dissertation, the form of user interface-facilitated serendipity is referred to as *UI-facilitated serendipity*. The use of serendipity in recommender systems provides vast potential for the research and development (He, Parra, & Verbert, 2016).

Most recommender systems work by presenting the most relevant recommendations first, with less relevant recommendations further down the list. The literature suggests that if the list of recommendations includes novel items that are less relevant, a user may experience serendipity by encountering unexpected, novel information (Kotkov, Wang, & Veijalainen, 2016). The current approach to recommender system-facilitated serendipity is algorithm-based, where the main idea of current approaches to UI-facilitated serendipity is to present users with information that gives them a picture of the randomness (re-ordering) of recommendations, and by highlighting them with their respective relevancy scores.

This method has worked in an algorithmic approach for facilitating serendipity (Kotkov, Wang, & Veijalainen, 2016) but the contributions of the user interface to facilitate this have not yet been explored. In contrast to the algorithmic approach, where serendipity facilitation is based on recommendation algorithms, UI-facilitated serendipity is a consequence of how that information is presented to users via data visualization methods and aided by novel user controls of that system.

A surprising recommendation is defined in terms of unexpectedness. As noted in (Kaminskas, 2014) and defined by (Herlocker, Konstan, Terveen, & Riedl, 2004), serendipitous information is both surprising and relevant. User interface designs that facilitate serendipity are discussed in detail in the related work section of this thesis. The assessment of serendipity experiences has evolved from solely algorithmic approaches to user-centric evaluations. With recommender systems gaining momentum, the opportunity has grown for beyond-accuracy recommendations to facilitate serendipity in these systems. Though several studies – including those outlined in this thesis – have been conducted to evaluate recommender systems, the literature lacks an assessment of the outcomes or deliverables (e.g., discoveries, inventions) to determine to what degree recommender systems might facilitate serendipitous outcomes.

Serendipitous findings in an academic research setting may help identify new research questions or reveal novel solutions to existing research problems. Therefore, this research aims to develop serendipity facilitation mechanisms for recommender systems that may be used in future products or services for educational settings to capitalize on the "aha moment". By prioritizing serendipity facilitation while designing and developing a recommender system user interface, this research transforms the concept of serendipity facilitation into a functional user interface.

As per the definitions for this thesis, a user interface that facilitates serendipity, like all serendipitous events, requires all the essential components of serendipity: a prepared mind is presented with novel information that triggers a connection by highlighting relevant information. In this process, the user interface enhances the likelihood of serendipity by presenting a user with information and recommendations that have a high chance of providing a serendipity experience. To test and develop the use of user interfaces for facilitating serendipity, I implemented user interface designs with four features: research article presentation, re-ordering for randomization recommendations, author-related work, and providing transparent user interface-level information that explained the recommendations presented to users. This additive approach increased the incidence of serendipity experienced by users of the recommender system. More information on user interface design is shown in the research methodology section of this thesis.

Prior studies have narrowly focused on serendipity facilitation via algorithm design, while user interface design for the same goal remains understudied. He *et al.* argue that an interactive recommender system possesses the potential for further advancement in serendipity facilitation (He et al., 2016a), though only a few studies of serendipity experience via interactive information systems, especially recommender systems, have been reported (Thudt, Hinrichs, & Carpendale, 2012) (Cleverley & Burnett, 2015).

Even fewer studies have used real-world academic research settings, limiting our understanding of recommender systems supporting serendipity in educational contexts. By studying recommender systems while users work on their tasks in an actual operational environment, the real-world utility and user experience can be evaluated. The subjective nature of serendipity demands new approaches to experimental design, evaluation techniques, and metrics to study serendipity facilitation. Therefore, the evaluation also requires subjective viewpoints such as sentiment analysis to accompany user experience data, beyond the conventional algorithmic performance evaluation typically conducted in research for recommender systems. Repeated measures of user experiences with the recommender systems enhanced the experimental rigor of these studies.

Serendipity has various forms that a person may experience, which have been discussed by McCay-Peet and Toms (McCay-Peet & Toms, 2015). Serendipity requires a prepared mind (*i.e.,* the user's current knowledge or experience), an openness or curiosity for exploration, evident triggers that engage the prepared user, the ability to make connections, and follow-up or action based on novel information or experiences, making this process useful but not necessarily timebound. All types of serendipity experiences benefit users, sometimes immediately and sometimes in the distant future.

It is argued that user interfaces that facilitate serendipity may provide positive user experiences (Rubin, Burkell, & Quan-Haase, 2011). This dissertation aims to address an evident research gap that advances user interface (UI) research to better facilitate serendipity in recommender systems. Improving the UI, including user controls and visualization (He et al., 2016a), may result in more useful, appropriate, and serendipity-facilitating applications of recommender systems. Previous research has shown that the user interface of a digital library can facilitate serendipity (Thudt *et al.*, 2012).

1.2 Research Context

The Human-Computer Interaction (HCI) Perspective to Recommender Systems

This thesis is positioned in the field of Human-Computer Interaction (HCI). The success of recommender systems has been attributed to many factors including HCI, which has progressed over the past decade (Calero Valdez, Ziefle, & Verbert, 2016). The focus of HCI for recommender systems is to develop personalized applications and improve experiences that pertain to diversity, serendipity, novelty, and exploration. The recommender system HCI research has focused on human factors such as user control, adaptiveness, effectiveness, and high-risk domains (Calero Valdez *et al.*, 2016). Optimized user controls create a meaningful user experience

(Harambam, Makhortykh, Bountouridis, & Van Hoboken, 2019). Modifications to user controls have improved the recommender system user experience (Guntuku et al., 2016).

The user interface contributes to the effectiveness of the recommender system to a great extent (Beel & Dixon, 2021). The commercial success of recommender systems has been highly visible on websites such as Netflix, Spotify, YouTube, Amazon, Twitter, and Facebook. These websites have gained value based on the capabilities of the interactive recommender systems (Millecamp, Conati, Htun, & Verbert, 2019). However, academia and educational technology platforms have yet to harness this potential by applying recommender systems to educational systems.

Cultural Context: Information and Communication Technologies (ICT) in the Higher Education Sector in Pakistan

Recommender systems are intended to support students in topic selection for class assignments, research articles, and theses. When considering recommender systems in academia, there are several factors to consider: differences in stakeholder expectations regarding research article recommendations, differences in recommender performance in various scenarios, comparisons of novel recommender systems with baseline recommender systems, and the need for open-source recommender systems to attract the interest of a broad research community (Beel & Dinesh, 2017). Beyond accuracy, other characteristics of recommender systems have evolved, such as usability, controllability, and transparency of recommender system behaviors, and the serendipity and diversity of the recommendations (Kaminskas & Bridge, 2016).

Most studies of recommender systems are conducted in developed countries (Taghavi, Bentahar, Bakhtiyari, & Hanachi, 2018). However, developing countries have a long way to go to adopt recommender systems (Liao *et al.*, 2018). There are no data available on recommender system use in developing countries and higher education institutions in developing countries rely on search-based systems, that are prone to an echo chamber effect (Fletcher & Nielsen, 2018). This is likely due to a lack of funds, insufficient information technology infrastructure, and low literacy rates. New technologies such as recommender system-based educational technologies are not common, and students are unable to benefit from serendipity facilitated by recommender systems. Electronic learning systems (e-learning systems) face challenges in higher education institutions in developing countries. These challenges include negative attitudes and perceptions about technology (Kim & Park, 2018). Studies can help better understand the technological challenges and the human-computer experiences in these countries.

Pakistan is a developing country with a developing information communication technology (ICT) sector. Though student performance has improved in higher education institutions where ICT is used (Ishaq et al., 2020), only 50% of higher education institutions use the ICT (Chandio, Hussaini, HussainAbro, Solangi, & Chandio, 2019). Higher education institutions in Pakistan do not use recommender systems to drive their academic activities, rather teachers and students are exposed to recommender systems on social media and through e-commerce platforms. Undergraduate students in Pakistan – whose age ranges from 18 to 22 years – have increased mobile phone density and computer use at the secondary school level supporting the notion that technology-driven processes can be successfully implemented at the higher education institution level.

By applying recommender systems facilitating serendipity in the higher education sector of Pakistan, this research opens a new field of serendipity-driven education. This research also helps to appreciate student and teacher perspectives about such technologies. Further, it helps identify opportunities where recommender systems might help to drive academic research. Developing user prototypes and fostering positive user experiences can play a vital role in adopting these technologies and improving research, innovation, and academic processes. This study investigates how recommender systems benefit the higher education sector, especially when applied to the discovery of research articles. Integrating a user interface that facilitates serendipity in a recommender system will provide an opportunity for students and researchers to experience serendipity in a new way. In higher education, serendipity facilitation via a recommender system UI has at least two potential areas that may benefit users: the serendipitous discovery of research articles that can be utilized in assignments, projects, and research theses, and aiding researchers in the identification of novel research ideas or solutions. Applications for serendipity in recommender systems in higher education can be found in libraries, research laboratories, and student learning processes.

The user studies for this doctoral thesis were conducted at the Institute of Management Sciences, Peshawar, Pakistan. The institute offers undergraduate and postgraduate degrees with a total student population of around 3,000 (both male and female). Most of the students come from the Khyber Pakhtunkhwa (KP) province of Pakistan. Student participants were in the final year/semester of their degree program. This ensured that the students queried were far enough along in their studies to have meaningful exposure to the research process and understood the needs for technologies in the research process.

1.3 Research Objectives and Questions

The primary objectives of this doctoral thesis are:

1. To design and develop novel user interface mechanisms to support serendipity in recommender system use (in higher education).
2. Study the impact of the novel user interfaces on higher education users working on academic tasks.

To achieve these objectives, the following research questions (RQ) are identified:

RQ1. What kinds of User Interface (UI) solutions of recommender systems can be used to facilitate serendipitous discoveries of a learner?

RQ2. How does UI-facilitated serendipity in recommender systems advance the objectives of higher education?

RQ3. What is the task load (*i.e.,* the difficulty a user experiences when attempting a task) of UI-facilitated serendipity of recommendation on learners?

The answers to these questions reveal critical elements to inform UI design, accounting for user experiences.

1.4 Research Approach and Methodology

The main research approaches used in this doctoral research are user experiments and constructive research. The user studies were conducted as field experiments in (a higher education institution). Using published and collected data, novel UIs were developed and then tested by users in field-experimental settings. Designing a UI for serendipity facilitation in recommender systems brings together advancements in technology, useful artifacts that serve as serendipitous content, effective recommender systems, and an effective user interface (Figure 2). User experiences with the serendipity-facilitating recommender systems were recorded and evaluated as subjective measurements (Questionnaire based on ResQue). The data were gathered and analyzed using statistical software (SPSS 20) and user sentiment data were analyzed to identify differences among the evaluated UI designs. The details about the ResQue Questionnaire are provided in the Annexure.

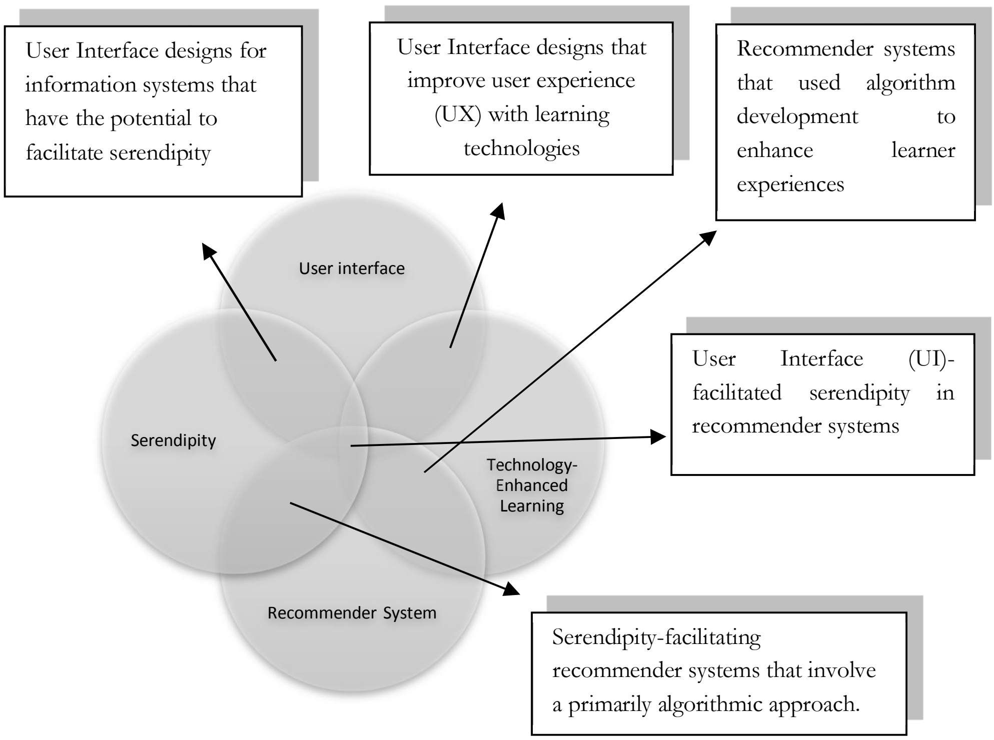

Figure 2. UI-facilitated serendipity in recommender systems

1.5 Key Contributions

Novel contributions of this work to the field include novel user interface designs for facilitating serendipity, a recommender system-based academic research process, and recommender system useability test reports for task load for learners (Table 1). The studies presented in this thesis provide a workflow of recommender system development, testing, and application, as well as new information about serendipity facilitation and technological perspectives in a developing country.

Table 1. Contributions of the Research Work

Contribution	Knowledge Gap	Output Work	Publications/ Communication
User Interface Design	There are no user interface designs for recommender system-facilitating serendipity	1) Developed a novel UI with user control-based re-order/ randomization features for serendipity 2) UI design aspects include: transparency, user control-based shuffle, and re-ordering features	Publication II, III, IV
Serendipity-based Academic Research Process	There is no recommender system driven academic research processes that also involve Serendipity	Analyzed serendipity-based work processes for academia	Publication I, II and III, VI
Usability Test Report	There are no studies on the task load of serendipity-facilitating recommender systems	Measured and reported the task load for UI of recommender systems for the research process. The recommender systems included serendipity-facilitating systems and others that could serve as baseline recommenders.	Publication IV and V

2 LITERATURE REVIEW

This chapter summarizes published literature on serendipity facilitation in recommender systems, digital environments, and higher education, with specific regard to user interfaces (UI). This literature review provides a framework and defines key concepts for the remainder of this thesis.

Serendipity has historical value in the scientific world. Understanding serendipity in research requires traversing through literature, where the historical value of serendipity is evident (Ban, 2006). The following overview of the literature reveals how serendipity has facilitated advancement and continues to do so in today's information technology-enabled research endeavors. Ban (2006) describes how serendipity contributed to the success of various discoveries, but until recently facilitating serendipity to advance scientific research has not been an explicit aim.

Studying and evaluating the serendipity of recommendations is challenging due to its subjective nature (Rubin *et al.*, 2011). Depending on the context and digital space, serendipity takes on different meanings and has different perceived values. Defining and measuring serendipity is still evolving (McCay-Peet & Toms, 2015). It is due to many reasons. First, serendipity is associated with a range of experiences, that are unexpected and positive items or events. Second, its observation has been reported to be challenging. Third, it is reliant on people’s memory, making it difficult to know what has changed (items or events) and what was simply forgotten.

Yaqub concludes that uncertainty is involved in every field of scientific discovery and “researchers have made unexpected and beneficial discoveries” (Yaqub, 2018), presenting various serendipitous findings underlying scientific achievements as evidence. This study further describes four distinct types of serendipity. He defines two types of user search actions and two outcomes that differentiate among these four types of serendipity. The key difference in action is whether users search with a problem in mind or not. When users search with a specific problem in mind, they can obtain two outcomes. The first is a solution via an expected or known method called *Walpolian serendipity,* and the second is a solution that occurs via a new route, i.e., *Mertonian serendipity*. When the user is searching without a problem in mind, the user may get a solution to a pre-existing problem that they were not currently considering called *Bushian serendipity*, or a user may find a solution that could be useful for a problem that may arise in the future called *Stephanian serendipity*. These four kinds of serendipitous experiences illustrate how "uncertainty and surprise" are components of the research discovery process. Understanding a socio-technical system is particularly important to understanding human factors in technology. Work by Ropohl asserts that serendipity has gained the attention of researchers to positively impact socio-technical systems. The concept of a socio-technical system describes the inter-relationship between humans and technology as a motivation for coping with problems in the work environment (Ropohl, 1999). Recommender systems that aim to facilitate serendipity should focus on the inter-relationship between humans and recommender systems. User experience is the prime focus of all serendipity-facilitating information system platforms. In a 2019 study by (Chen, Yang, Wang, Yang, & Yuan, 2019), serendipity improved user satisfaction with information systems. The authors highlighted the utility of beyond-accuracy experiences (*i.e.,* serendipity, novelty, diversity). Among the three experiences, serendipity provided the most significant impact on positive user experiences. User's curiosity plays a vital role in building relationships between novelty and serendipity that leads to positive user satisfaction. The authors argued that serendipity could serve as a new element to improve user satisfaction with recommender systems. This work suggests that there exists substantial potential in re-engineering current recommender systems using serendipity facilitation to improve the user experience. An article by Olsson *et al.* (2013) implies that also recommender systems could benefit from experience-driven design methods based on specific user experiences.

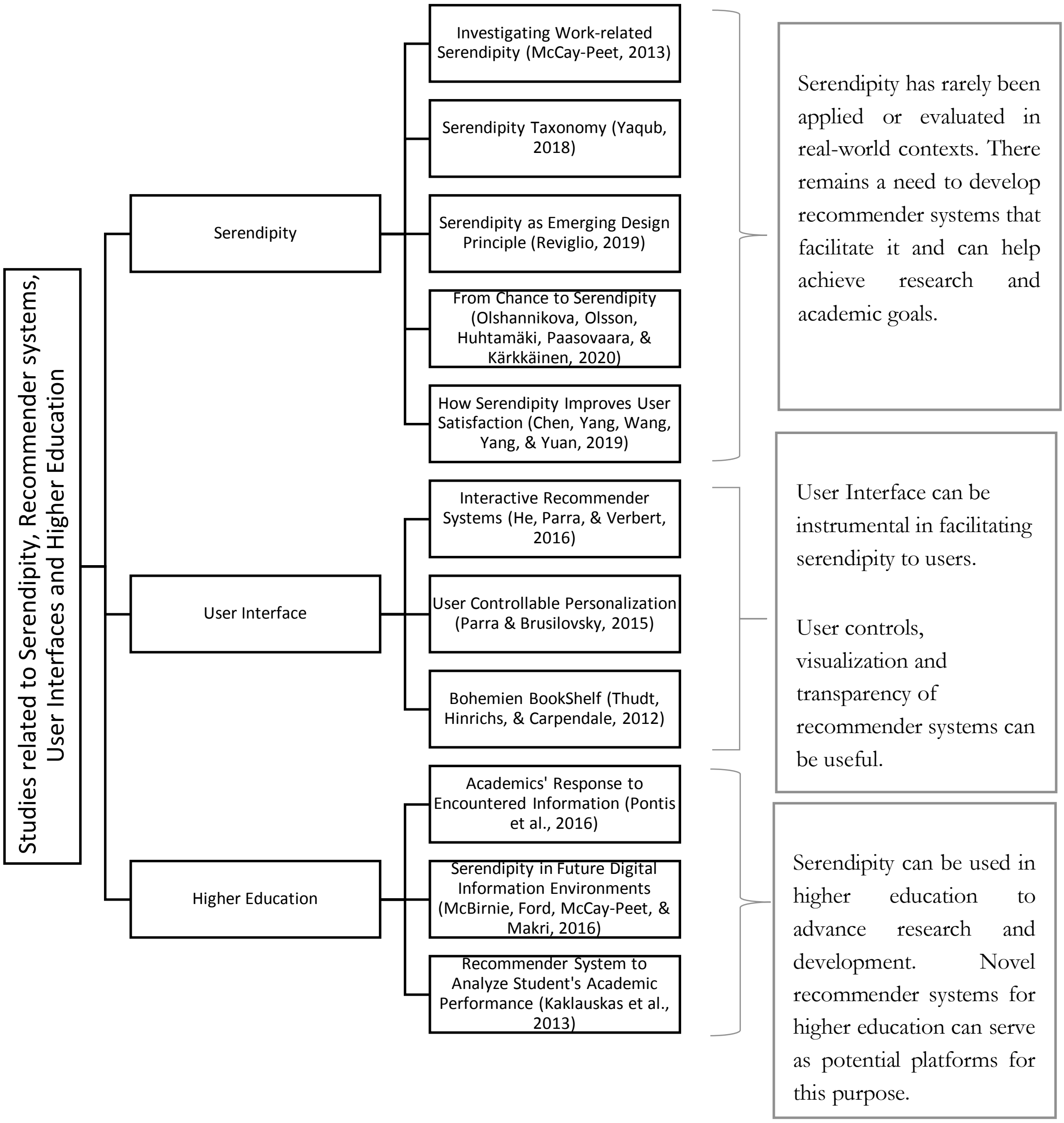

Figure 3. Literature map

The articles listed in Figure 3 are the literature sources used in this thesis to describe the current knowledge regarding user interface-facilitated serendipity. These sources can be categorized into three primary topic areas: serendipity, user interfaces, and serendipity in higher education. In Figure 3, each article (branch) contributes to the field of research that forms the foundation for this doctoral thesis and the publications included in the portfolio in Part B of this thesis.

2.1 Understanding Recommender System User Interfaces and Serendipity

This section covers serendipity and challenges associated with the digital environment and higher education.

2.1.1 Serendipity in Digital Environments

The digital environment can be defined as "a context, or a 'place,' that is enabled by technology and digital devices, often transmitted over the internet, or other digital means" (Kotsanis, 2018). There has been substantial work on understanding serendipity in the digital environment (McCay-Peet, 2013). The key focus of the work by McCay-Peet is the way digital environments can facilitate serendipity. The author has established how serendipity– from the prepared mind to the experience of serendipity – connects users with surprising, yet valuable information in a complete serendipity cycle. This work supports the notion that understanding human psychology and designing technology using that information can facilitate artificial serendipity. In another study, McCay-Peet and Toms develop a single model of serendipity that includes trigger, connection making, and follow-up (McCay-Peet & Toms, 2015). This model provides a framework for technologies, especially for interactive information systems that can potentially facilitate artificial serendipity. Interactive system designers can use this understanding of triggers, connection making, and follow-up behaviors to develop and advance technological components that can perform these tasks and improve the serendipity cycle. Another study on developing a digital environment (McBirnie *et al.,* 2016)*,* discusses the critical implications and dependencies of the digital environment on serendipity. The authors conclude that serendipity-facilitating technologies can be developed by building on the understanding of serendipity.

One study on serendipity in recommender systems discusses the types and manner in which serendipity is experienced (Kotkov, Veijalainen, & Wang, 2016). Serendipity facilitation faces several challenges that should be considered when serendipity-facilitating systems are developed. First is the subjective nature of serendipity. Serendipity takes on a new meaning in different contexts in various recommender systems. Second, the authors argue that the dynamic emotional dimensions of users (the user's mood or state of mind) make it challenging to measure serendipity objectively. Additionally, contextual factors play a significant role in measuring and evaluating serendipitous experiences. With these factors in mind, the authors attempt to define a broader scope and situation with which serendipity can be framed. There are additional challenges associated with serendipity: predictability of serendipity, passive consumption of serendipitous information, the redundancy of information, and instant gratification that users experience due to receipt of serendipitous information (Reviglio, 2019). Therefore, serendipity-facilitating recommender systems should be measured over time, with approaches that record the user interaction, experience, and sentiments.

2.1.2 Serendipity and Higher Education

This section introduces literature related to serendipity and scholarly pursuits, with a focus on the higher education sector. Since this doctoral thesis focuses on studying and applying serendipity in the educational environment, it is important to understand how various technologies have facilitated serendipity in this setting. This section also includes pioneering user interface studies in this sector.

One context for serendipity in higher education is book discovery. Book discovery and user interface studies by Thudt, *et al,* pioneer serendipity and information systems in the scholarly context (Thudt *et al.,* 2012). A key focus of their work is facilitating serendipitous encounters through interactive information systems. Their work is considered critical for artificial serendipity facilitation via UI design. The work attempted to advance interactive design far beyond accuracy alone (beyond-accuracy experience), increasing the chance of resource discovery. They found that visualization of book data increases a book's discoverability. Their work is also one of the first to apply serendipity to academic pursuits, finding enormous potential in information visualization techniques that can be used to develop artificial serendipity capabilities for use in academic settings. A study by Sugiyama & Kan (2011) worked to advance the understanding and utility of serendipity for scholarly work. They modified author profiles to facilitate better serendipitous encounters.

A study by Pontis, *et al.,* focuses on serendipity and academic goals, emphasizing academic needs and their alignment with serendipity capabilities (Pontis *et al.*, 2016). The authors argued that serendipity is desired more by information system users when there is coherence in "added information and the current focus of the users (state of mind)." This article analyzed the contextual factors (*e.g.,* location, activity, and focus) that impact serendipity – and the way it is received by users – in academic settings. Another study argued that serendipity is essential to library and scholarly pursuits (Carr, 2015). This work presented readers with different views of serendipity in library spaces, using perspectives from various researchers and authors. The author reported that some participants in the study viewed serendipity as relevant while others viewed it as a system detracting from the core function of libraries. The author viewed libraries as "inspiration architecture" rather than "information architecture," underscoring the need for technologies like serendipity-facilitating recommender systems that foster the role of libraries as inspiration.

Recommender systems are used in the higher education sector (Obeid, Lahoud, El Khoury, & Champin, 2018). Nonacademic but commercially available media such as

YouTube (video recommendations) and Amazon (books recommendations) also provide ample opportunity for higher education stakeholders to experience receding system-driven higher educational processes. A 2013 study that evaluated recommender systems for student performance (Kaklauskas *et al.*, 2013) demonstrated the importance of recommender systems in the education sector. The study revealed that recommender systems are instrumental in managing student performance. Another study showed how course enrollment can be completed through a recommender system (Anuvareepong, Phooim, Charoenprasoplarp, & Vimonratana, 2017). In this study, the recommender system suggested courses to the students that were relevant to the student's academic profile. These studies provide examples of uses for serendipity in streamlining educational processes. However, there remains a need for studies evaluating real-world applications for serendipity-driven academic endeavors and research activities.

2.2 Related Work in UI-Facilitated Serendipity

A review of the literature reveals that there has been no systemic effort or model from which to develop UI-facilitated serendipity in recommender systems. However, information systems have been created to facilitate serendipity experiences. Thus, the literature on UI-facilitated serendipity has been presented in two parts. The first part consists of recommender systems that have facilitated serendipity experiences for users. The second part covers information systems as an example of UI-facilitated serendipity in other contexts.

2.2.1 Interactive Recommender Systems

Research aimed at serendipity facilitation lacks a methodological approach toward the design of UI-facilitated serendipity of recommendations. Additionally, the literature shows that user control and serendipity have not been studied to design impactful applications. In a study about interactive recommender systems (He *et al.*, 2016a), the authors elaborated on the user control and visualizations of recommendations. Most recommender systems are accuracy-oriented, they only recommend items related to the search given. The authors discussed the taxonomy of interactive recommender systems because user controls are primarily utilized for accuracy-oriented recommender systems. The work on recommender systems is dominated by algorithmic advancement. Most research focuses on user interfaces involving ranked list manipulation with a fixed set of visualizations. Further, the survey presented in He's paper (2016) focused on the structure and usage of state-of-the-art interactive recommender systems and their evaluation.

Serendipity Facilitation and the User Interface in Recommender Systems

User control in recommender systems has been previously studied, primarily aimed at delivering a better user experience. One study focusing on user control of recommender systems shows context-based visualizations of recommender systems with controllability elements (Bostandjiev, Donovan, & Höllerer, 2012). The study demonstrated that controllability improves user perception and trust, improving user experience. Similarly, studies on trust and discovery in recommender systems using Spotify music recommender system user interfaces revealed that user controls enhanced trust in contemporary music discovery through the radar visualization (Millecamp, Htun, Jin, & Verbert, 2018). Parra and Brusilovsky argued that user control is instrumental in the recommender system personalization (Parra & Brusilovsky, 2015). This 2015 study used a Venn diagram-based layout for recommendation visualization in a user-controllable recommender system. The study concluded that user control encourages user engagement with the recommender system. The study was a departure from the ranked list recommendation. (Parra & Brusilovsky, 2013b) presented a user-controlled recommender system and Venn diagram-based visualization of the recommender system to support the exploration of recommendations. Recently, the recommender system and graphical user interface (GUI) effects have reported that user controls have a positive impact on the user experiences (Beel & Dixon, 2021). The authors noted that more studies are required to fully understand the UI of recommender systems.

Multiple studies have revealed potential roles for the user interface to improve serendipitous encounters for recommender system users. In a study of user interfaces of recommender systems, Parra and Brusilovsky evaluated the user interfaces on their recommender system app called "Conference Talk" (Parra & Brusilovsky, 2013b), focusing on the contextual relevancy of a recommendation. The recommender systems tested use a UI with a Venn diagram representing distinct categories for output. This pioneering work was one of the first to test UI interfaces for beyond-accuracy recommendations in recommender systems. This work supports user interface implementation where the UI is given a more significant role, beyond merely displaying recommendations. Another study on user-controlled recommenders focused on the user preferences (Loepp, Hussein, & Ziegler, 2014). A key contribution of this article was the suggestions for how to handle "Cold Start" (recommender system not knowing the users' personal preferences) by implementing explicit choice-based preferences. Studies on user interactions with recommender systems and explicit preferences have been discussed previously by (Knijnenburg, Reijmer, & Willemsen, 2011). The primary objective of this study was to evaluate multiple interaction techniques. This study demonstrated how user interactions affect recommender system performance.

2.2.2 Interactive Information Systems

The main objective for analyzing and contextualizing literature focused on serendipity and interactivity in information systems is to identify clues provided by these articles to understand better how user interface design – including user control and visualizations – can facilitate serendipity in recommender systems. UI visualizations have been the focus of many studies, showing that different visualization techniques elicit varying results with different levels of recommendation diversity. It is important to use knowledge of user interface design in non-recommender systems (information systems) to inform the design of user interfaces for serendipity facilitation for recommender systems.

Serendipity Facilitation and the User Interface in Information Systems

Research on interactive information systems shows that implementing specific features, such as Venn diagram-based visualizations, scatterplot exploration-friendly visualizations, and user controls can help users experience serendipity while exploring recommended items. Furthermore, this work applies to academic recommender system UI design because the information systems for applications such as book discovery are closely related to academic applications. One study on augmented reality demonstrates that discovery-oriented user interfaces can help facilitate serendipity (Bach, Sicat, Pfister, & Quigley, 2017). Bruns *et al.* (2015) showed that graph-based visualizations for information systems help users easily find relevant items. Alexander *et al.* (2015) evaluated layer-based information exploration that helps users navigate items in their work. Rädle *et al.* (2012) implemented 2-dimensional scatterplots for information visualization that ultimately helped facilitate serendipity. Calero Valdez *et al.* (2015) studied author-centric bubble charts for information visualization to facilitate discovery. Kleiner, Rädle, and Reiterer (2013) evaluated UIs with real-life settings. The techniques they describe helped promote discovery through a user-friendly presentation. Dumas *et al.* (2014) studied a realistic UI design that helps users discover artwork.

Kleiner *et al.* (2013) used chains, discovery circles, and timelines in a UI design to facilitate book discovery. Similarly, Cleverley and Burnett (2015) present a graph-based presentation that facilitates item discovery. These pioneering works on user interfaces inform future modifications for improved serendipity facilitation.

Serendipity facilitation and Measurement

Serendipity facilitating UIs of both information and recommender systems have been evaluated using user studies. These involved feedback from users that indicated that serendipity had been experienced by the users.

Table 2. Overview of Serendipity Facilitating User Interfaces

<table>
<tr><th>Study</th><th>User Interface Design</th><th>Serendipity measurement</th></tr>
<tr><td>(Parra & Brusilovsky, 2013)</td><td>Venn diagram-based recommendations visualizations</td><td rowspan="5">Data collection from users and statistical analyses

The studies also collected user objective datasets such as interactions with recommender system user interfaces, however, user experience datasets (subjective data) were instrumental in determining serendipitous recommendation experiences</td></tr>
<tr><td>(Loepp et al., 2014)</td><td>Grid-layout based recommendations presentation</td></tr>
<tr><td>(Bostandjiev et al., 2012)</td><td>Root-leaf approach-based recommendations visualizations</td></tr>
<tr><td>Bruns et al. (2015)</td><td>Connected graph-based recommendations visualizations</td></tr>
<tr><td>(Millecamp et al., 2018)</td><td>Radar chart-based recommendations visualizations</td></tr>
</table>

Designing the User Interface

The visualizations and controls of serendipity were discussed in Publication 1 and included as part of this thesis portfolio (Afridi, 2018). This article was a pilot study that aimed to understand the user preferences at the Institute of Management Sciences for a user interface that showed purposeful recommendations. In this study, users were presented with six different ways to visualize recommendations: pie charts, lists, scatter plots, graph-node, set-based and bubble charts. Pie charts were the preference of the majority of users for serendipity accuracy-oriented recommendations.

The review article included as part of this thesis portfolio reviewed several recommender system user interfaces that facilitate serendipity. These user interfaces incorporated components to create randomization to increase the likelihood of triggering a serendipitous experience. This review (see review article in Part B of this thesis) revealed that some controls and visualization techniques facilitated serendipity while others were less successful. This analysis of prior research provides a glimpse into what is known regarding user interfaces for serendipity facilitation, information that could be built upon, and inform UI design. Primarily, these user interfaces utilized controls that allowed users to randomize the recommendations list, explore the recommendations list, or navigate through the recommendations. The recommender systems that were used to facilitate serendipity were not specifically designed for this purpose but yielded serendipitous experiences. Key visualization end-user control elements included:

- List view of recommended items
- Graphs revealing connections among recommended items
- Venn diagram-based recommendations visualizations
- Radar chart-type recommendations visualizations
- Charts and widgets

Fundamental UI Design Attributes of Serendipity Facilitating User Interfaces

From this review, a key question arises: how can user interfaces for serendipity facilitating recommender systems be designed and implemented? Moving beyond previous research, in designing a novel user interface, I first developed user controls and recommendation visualizations were implemented to promote the trigger and connection making to facilitate serendipity. The user controls and visualizations included charts that contained author support, dates, related work, and transparency about how recommendations were determined. The user interface components included in this research were buttons, drop-down lists, lists, transparency bubble messages, and charts. The user interface components studied in background research are presented in the following table (Table 3).

Table 3. User Interface Components and Serendipity Facilitation

User Interface Capability	Functional Service
Button	Re-rank recommendations
Drop-down List	Selection and presentation of recommendations
Scrolling List	Selection and presentation of recommendations
Radio Button and Checkboxes	Filters and restrictions
Function Transparency Box	Following a researcher or influencer

Transparency and Recommender Systems

Transparency in recommender systems has improved user experience, playing a vital role in advancing UI design. Many opportunities exist to apply transparency in recommender system user interfaces to enhance user trust (Nilashi, Jannach, Ibrahim, Esfahani, & Ahmadi, 2016). One study showed a positive association between user interaction and perceived transparency when users aim for a beyond-accuracy experience (Tsai & Brusilovsky, 2017). Similarly, a study introducing Talk Explorer, a visual recommender system, revealed a positive association between transparency of recommendations and user experiences (Verbert, Parra, Brusilovsky, & Duval, 2013). Kizilcec reported that transparency resulted in increased user trust in the software (Kizilcec, 2016). An increasingly intelligent system requires transparency to maintain user trust.

Serendipity-facilitating recommender systems, specifically UI-facilitated serendipity in recommender systems, require leveraging transparency, a concept that has not been sufficiently studied (He, Parra, & Verbert, 2016b). Many studies have been conducted concerning recommender system transparency and controllability (user control). However, transparency and diversity within the context of serendipity have not been explored. The recommender systems studied for transparency in the literature review by He, Parra, and Verbert (2016) were equipped with a variety of visualization techniques including node-link diagrams, set-based views, and radial views. The authors did not identify articles that evaluate transparency and serendipity-facilitation in recommender systems. A novel functionality requires increased trust. As serendipity facilitation is not generally the primary interest when using recommender systems, transparency in this process can contribute toward user trust and subsequent adoption.

Context, Recommender Systems, and Serendipity

Contextual information may influence user choices. This idea has rarely been investigated for serendipity-facilitating recommender systems. The primary purpose of context is to add relevancy to the serendipity-facilitating process. Contextual information presented to users can promote reflection or trigger an idea.

A study by He *et al.* (2016) discussed the value of contextual information in interactive recommender systems. The idea behind contextual information usage in recommender systems is that there is a need for recommender systems to exploit situational awareness and adapt or filter the recommendations accordingly. Another study presented a framework for computational serendipity using a model that incorporates surprise, value, and curiosity to present a personalized serendipity experience (Niu & Abbas, 2017). This work showed the importance of context in serendipity-facilitating systems. The prototype described by Niu and Abbas has been implemented in the health news domain.

Work on context-aware music recommendations facilitating serendipity takes a primarily algorithmic approach, but the contextual information was vital in presenting users with relevant recommendations (Wang *et al.*, 2014). Another group studying context-aware recommender systems concluded that contextual information is a vital and rarely explored factor contributing to serendipitous encounters in recommender systems (Haruna *et al.*, 2017). Bawden, who studies serendipity in information systems, advocated for using contextual information to facilitate serendipitous encounters (Bawden, 2018). Wang, Meng, and Zhang explored a variety of contextual factors, including physical, user-specific, and social contexts. They argued that recommender systems must continue to use contextual information to personalize the recommender system output (Wang, Meng, & Zhang, 2012).

User Control, Recommender Systems, and Value

User control of a recommender system is key to user-driven serendipity processes. The user control ensures that serendipity facilitation is at a user's discretion, where users can turn off serendipity-facilitating features when desired. Various buttons or widgets help users achieve this task (He et al., 2016a). Most studies have focused on the user interface of recommender systems with features such as buttons and sliders, pie charts, interactive graphs, and interactive tabular recommendation lists. Parra and Brusilovsky advocated for more personalization in user controls for recommender systems (Parra & Brusilovsky, 2015). This study, which used a Venn diagram to present recommendations to the user, revealed that user control for recommendations personalization enhances serendipity capabilities. One study (Verbert *et al.,* 2013) assessed visualization transparency, context, and user controls in recommender systems. This study also explored interactive visualization features and showed that user control enhances recommendations exploration among users.

2.3 Summary and Reflections

The literature covered in this chapter helps frame the concept of serendipity facilitated by recommender system UIs. The study of serendipity facilitation by UI of recommender systems is relatively novel compared to conventional algorithmic approaches. There is still much work to be done to understand and design interfaces suitable for real-world academic applications. This requires testing in suitable real-world scenarios. Developing real-world scenarios for testing presents its own set of challenges, such as identifying a large enough group of test subjects and the logistics of translating those findings to a novel serendipity-facilitating recommender system.

Serendipity improves user satisfaction (Chen *et al.,* 2019), however, the user interface must be modified to realize the potential of serendipity in an academic research context. The challenge of initiating and changing the current research processes to implement UI-facilitated serendipity is substantial. As discussed in the literature, researchers must keep in mind that serendipity is a subjective – and evolving – concept. Developers should consider moving toward a more user experience-centric development process. The user controls and visualizations that have been used in state-of-the-art recommender systems show that serendipity has not been studied with consideration for user controls, transparency, and contextual information. Recommender system UI designs for transparency can establish trust in recommendation processes. This literature review supports the notion that beyond-accuracy experience is essential for the advancement of recommender systems in higher education as it has been in many other fields where recommender systems and serendipity are applied. Furthermore, the value of serendipity capitalization via technology is established in the literature, but serendipity facilitation needs more than optimized algorithms with users passively waiting for "aha" moments.

To date, the user interface research for beyond-accuracy experiences has been dominated by diversity and exploration of recommendations. Although serendipity has been a component of published studies, serendipity itself was not the focus of these studies. Further, there are insufficient studies evaluating the contributions of user controls to serendipity. Some attention has been given to the interactivity and diversity of recommendations, but few studies have focused on the effect of transparency, which is useful in establishing user trust.

While UI-mediated serendipity facilitation offers several research opportunities, there remain substantial challenges. First, there is a cost associated with the facilitation of serendipity in recommender systems. To implement these systems, users must appreciate the value and utility of serendipity in their research and academic endeavors. The need for value- and impact-orientation of recommender systems is essential. This involves developing recommender systems that provide greater value for users and understanding user context along with the algorithms. The lack of ICT infrastructure is a major hurdle in implementing recommender systems in higher education. The main ICT items to address are the acquisition of data for recommender systems, access to recommender system platforms, and connectivity with the main academic digital libraries. Awareness of these technologies in developing countries is another hurdle. All these factors must be considered to develop and promote implementation in higher education settings in a developing country.

3 RESEARCH APPROACH, PROCESS, AND METHODS

This chapter describes the approaches utilized during this doctoral research, detailing how individual studies were conducted. Further, this chapter provides an overview of the philosophical approaches as well as the criteria used for evaluating recommender system user interfaces during development. A detailed description of methods for data collection and standardization along with the conceptual approach and the broader context is included.

This research was conducted in multiple phases (Figure 3). A total of ten recommender system UIs were evaluated. These include six that are commercially available and three high-fidelity prototypes explicitly developed for this doctoral research. One low-fidelity prototype was also generated in these studies. All the commercial platforms evaluated are already used in educational systems in Pakistan.

3.1 Study Phases

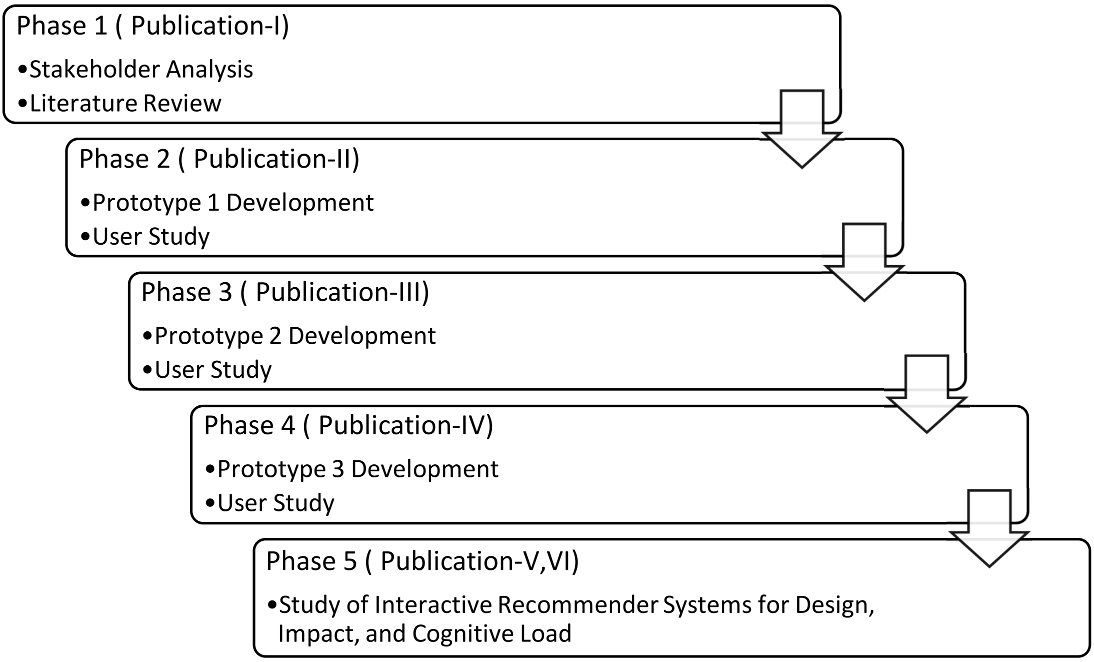

Figure 4. Study Phases

Phase 1

The stakeholder analysis and literature review helped to identify critical research problems. Stakeholder analyses in this thesis were conducted in an academic institution in Pakistan. This involved understanding recommender system usage and applications in academia.

Phase 2

The prototype developed in Phase 2 helped to identify and establish post-processing of recommendations by re-ranking the top N-List of recommendations. Mr. DLiB, a RAAS (Recommendations-as-a-Service), generated the top N-List. The prototype provided user controls with randomization functions. The prototype also aimed at improving connection-making, which was achieved by presenting users with an author's other works and contribution charts, recommended articles, and randomized recommendations.

Phase 3

The prototypes (Figures 12 and 13) developed in Phase 3, had all the functionality of the previous prototype with the addition of features to facilitate serendipity experience triggers, which were accomplished by enhancing the transparency of the recommender system.

Phase 4

This prototype (Figure 14) had all the features of the previous prototype with additional randomization charts showing relevant and serendipitous recommendations.

Phase 5

This phase involved studying the task load with related experiments aiming for serendipity facilitation via the user interface.

3.2 Research Methodology

This thesis work utilized a constructive research methodology (Figure 5) (Zimmerman, Forlizzi, & Evenson, 2007), which describes research methodologies where the research problem has no known solutions or there exists only partial solutions. In this case, the solution to the problem of inadequate UIs to facilitate serendipity in higher education recommender systems is in the prototype stage and not ready for deployment (Oulasvirta & Hornbæk, 2016). This research applied the constructive research paradigm by applying the following steps: finding a research problem, understanding the problem domain, innovating a solution, revealing the solution, demonstrating the solution's research contribution, and analyzing the applicability (McGregor, 2018). Experiments conducted as part of this research also follow an experimental research process as described by Gergle and Tan (Gergle & Tan, 2014). To this end, user studies were conducted as experiments with a repeated-measures design. Novel prototypes were compared to standard baseline recommender system user interfaces. The user studies were quantitative, but sentiment analyses were also conducted in some user studies, making them mixed approached user studies.

Research conducted as part of this thesis follows the quality standards outlined below (Naukkarinen, 2015):

- *Measures of Truth Value*: The internal validity of the research process has been maintained. The user studies were conducted according to HCI (recommender systems) experimental standards. The experimental designs are based on well-defined, published standards (Gergle & Tan, 2014; Rind, 2011), as described in more detail below.

- *Measures of Applicability*: The research can be applied to digital libraries, online bookstores, and e-commerce websites as well as the real-world academic contexts we investigate in this thesis.

- *Measures of Consistency*: The consistency has been addressed by adopting a repeated-measures design. For the user interface prototype evaluations, each user interface was evaluated two separate times. These data were accompanied by qualitative feedback in the form of sentiment analyses. The repeated measures design for the evaluation of user interfaces facilitating serendipity is based on work by Lix and Sajobi (Lix & Sajobi, 2010).

- *Measures of Utility*: The user experience of students was recorded on a Likert scale, recording the utility of the user interfaces and the serendipity concept of the users. The questionnaires used are standardized and include the NASA-TLX (Hart & Staveland, 1988) and ResQue (Pu, Chen, & Hu, 2011).

- *Reliability of Results*: The studies were conducted in a reputable academic environment, the application of methods is consistent, and the user studies were conducted with multiple users over the course of this thesis research. The results have been published in peer-reviewed journals, conference proceedings, and a book chapter.

- *Measures of Neutrality*: Only users willing to fill the questionnaire were given the questionnaires for feedback. The feedback has been collected from various classrooms over two years. The user experience data includes comments that explicitly discuss the user interface designs and have been presented in each article's annexures.

- *Validity of Results/Findings*: The choice of appropriate measurement methods has been considered. This is reflected in the literature review and the user studies conducted. The details of the measurement methods are discussed further in the study details. Power analyses to determine the sample size are discussed in more detail later. The standards followed are presented in Shani and Gunawardana (Shani & Gunawardana, 2011).

- *Novelty and Contribution*: This research contributes to developing user interfaces for recommender systems that can facilitate the serendipity of recommendations.

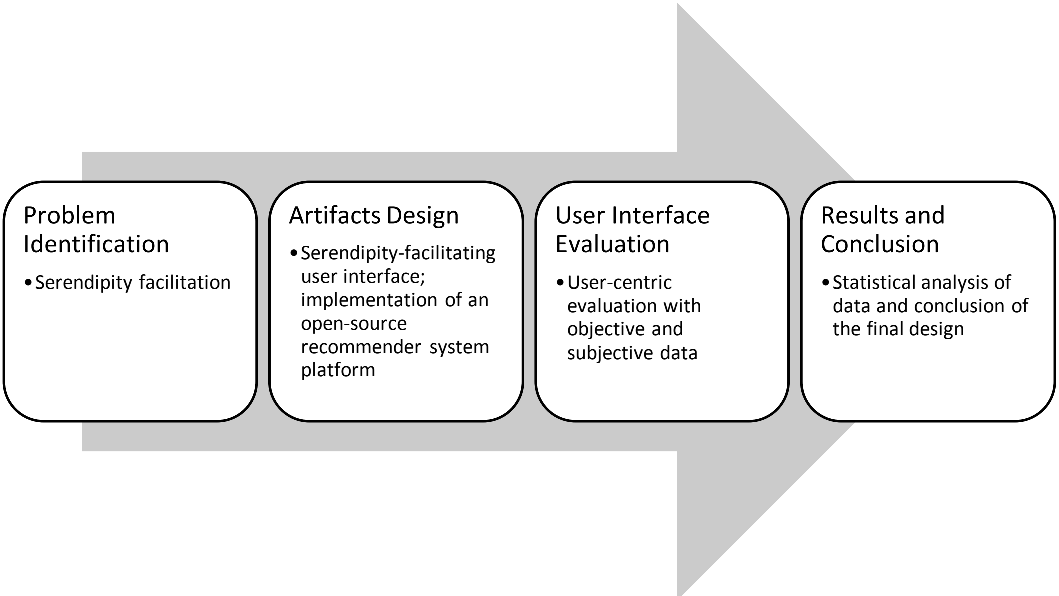

Figure 5. Research Methodology

Overview of Designed Artifacts

This section discusses the characteristics of designed artifacts for this research. The artifacts are user interface (UI) designs, serendipity-based academic research, and usability test reports.

1. User Interface design

Serendipity-facilitating UI design for recommender systems is presented in Figures 6 and 7. The user interface design is based on the principle of recommendation randomization (post-recommendation processing) for facilitating serendipity for the user. The recommendation is a list of top items in terms of relevance (top-N-list), recommending research articles.

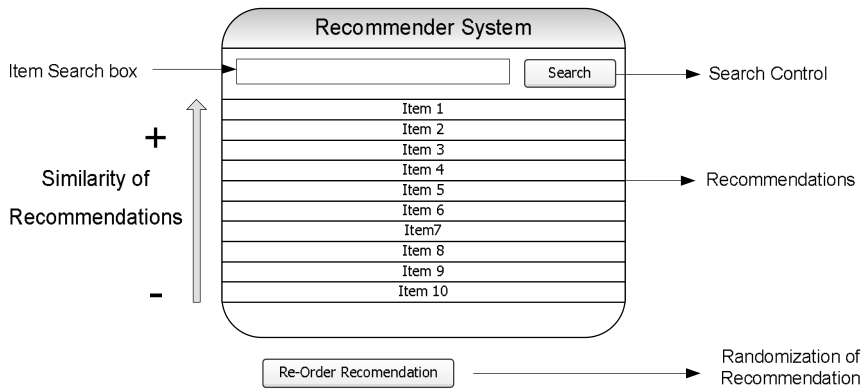

Figure 6. Recommendation Randomization of Top-N List via User Control

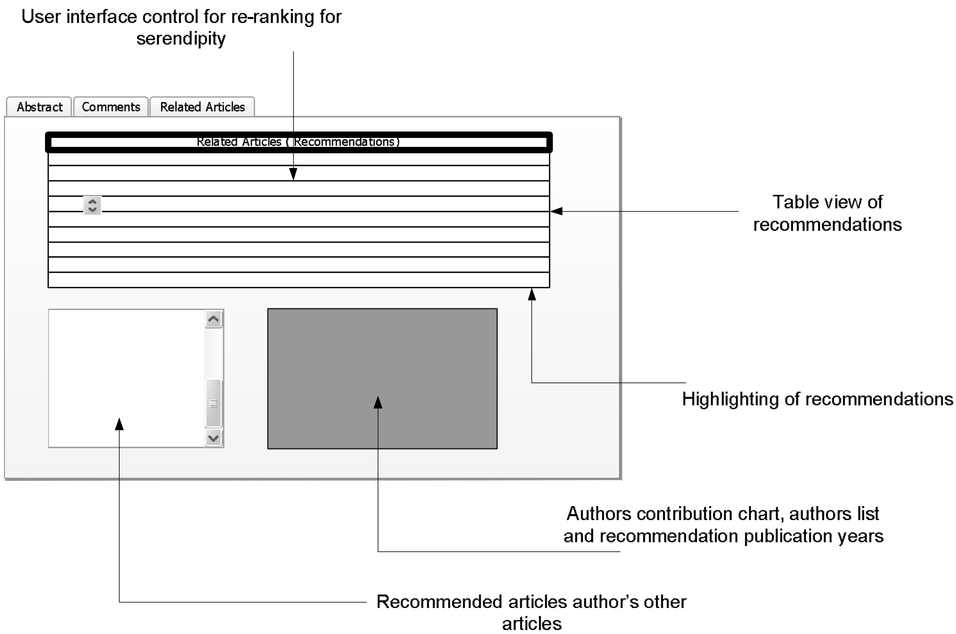

Figure 7. Recommender System UI Design

Researcher and similarity scatterplots allow the user to look for authors where there is a potential for serendipity to take place. As mentioned in the articles in the thesis portfolio, the primary approach for serendipity facilitating recommender systems utilized "UI color, colors-based prominence, and table controls to facilitate a nearby serendipity effect. An explanation of the various menus will add to the transparency of the recommender system user interface." This is described in more detail in the second portfolio article.

The number of downloads, number of research papers viewed, or number of user controls involved in diversifying results did not make a significant difference during the duration of these experiments. However, a serendipitous outcome from these encounters might occur in the distant future; a research article encountered today may increase the likelihood of serendipity in a future encounter. These parameters are still worth evaluating in future studies.

2. The serendipity-based academic research process

The serendipity-based academic research process covers the steps and usage of the recommender system in the topic selection for student theses and class reports. The recommendations are articles recommended to students based on an author's other work.

Figure 8. Research article recommendation process

3. Usability test report

User interface-facilitated serendipity impacts user task load. The usability test report includes the task load and user experience data in academic learning environments.

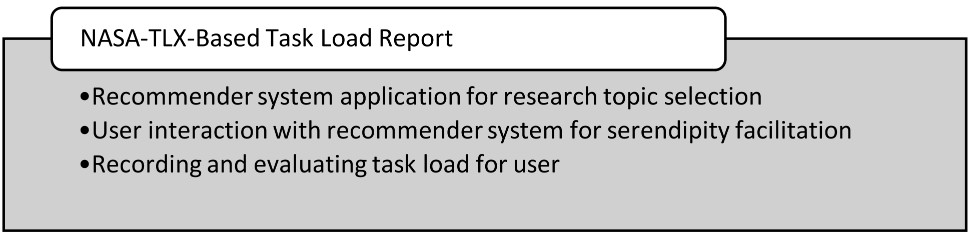

Figure 9. Task load report

3.3 User Interface Evaluation Standards

Recommender system evaluation has been discussed by various authors and addressed for recommender systems (Gunawardana & Shani, 2015; Tintarev & Masthoff, 2012), including matrices to evaluate the serendipity of recommendations (Murakami, Mori, & Orihara, 2008). These frameworks and matrices provide a consistent means to evaluate the user interface of recommender systems.

In this research, the ResQue framework was applied to evaluate the user experience with the recommender system. The ResQue (Pu *et al.*, 2011) framework provides a user-centric approach to assessing the quality of user experience. It measures perceived recommender system quality, as well as beliefs, attitudes, and behavioral intentions about the recommender system. A ResQue-based questionnaire was used to evaluate the user experience of prototypes and commercially available serendipity-facilitating recommender systems developed and tested during this research. The questionnaire can be applied to evaluate distinct kinds of recommender systems independent of a specific algorithm (recommendation engine). Responses to ResQue questions are based on a five-point scale format, ranging from strongly agree to strongly disagree (Pu *et al.,* 2011).

The NASA-developed NASA-TLX (Task Load Index) was initially introduced for evaluating the human mental workload of spacecraft controls (Hart & Staveland, 1988). The standard provided a measure to evaluate the spacecraft design and cognitive user load while using it. It has helped interface designers and spacecraft/aircraft designers evaluate cognitive user load in their designs and is a critical component of improving user interface designs. Recent literature reports on its application in user interface studies to evaluate cognitive load(Ramkumar et al., 2017). NASA-TLX has been applied to study the cognitive load of user controls and visualizations of recommendations (Amato, Moscato, Picariello, & Sperlí, 2018; Machado et al., 2019; Su et al., 2019).

In recent years, sentiment analyses have been critical for evaluating recommender systems (Erdt, Fernandez, & Rensing, 2015). Various software platforms are now available and provide an effective computational route to evaluate subjective dimensions of recommender systems. Sentiment analysis works by providing the software with user statements about the recommender systems. The sentiment analysis software provides a qualitative measure of user sentiments about the recommender system based on users' feedback comments. Sentiment analyses provide a qualitative evaluation of the recommender system user interface, allowing researchers to investigate dimensions of UIs that other evaluation techniques have missed. In this research, the recommender system users were asked to provide feedback about their experience. The comments received were evaluated via sentiment analyses.

Experimental platforms developed for UI-facilitated serendipity

The JabRef "Related Articles" tab was selected as the evaluation platform for high-fidelity user interfaces. The GraphLab Framework was used as the platform for low-fidelity user interfaces. The recommender system details are presented below.

JabRef reference management software was chosen as an experimental platform for serendipity experience evaluation. The main reason to select this platform was to observe the serendipity experienced by users (*i.e.,* students and teachers) during academic-related tasks (*e.g.,* research). JabRef is open-source software under the MIT license, providing an opportunity to develop software iteratively for successive prototypes. Reference management software allows users to store literature relevant to their research needs. Stored literature bibliographies were provided as input to the recommender system for generating a recommendations list. This list can further be manipulated for serendipity-facilitation. JabRef uses Mr. Dlib's recommendations-as-a-service (RAAS).

Both JabRef and GraphLab Framework are based on open-source technologies and can be re-engineered to suit the study aims. However, both resources have limitations. The available list of recommendations in JabRef is limited to seven, and the GraphLab-based recommender utilizes Bookcrossing, a very sparse data set. This can create bottlenecks when UI-driven serendipity is fully operationalized. However, it is possible to integrate other recommendation service platforms and add new user controls. One additional challenge is that JabRef is based on the RAAS Mr.DLib and, thus, if any problem arises with Mr.DLib, users will lose service. Similarly, GraphLab support is limited to external APIs (Application Programming Interface) and UIs cannot be re-implemented.

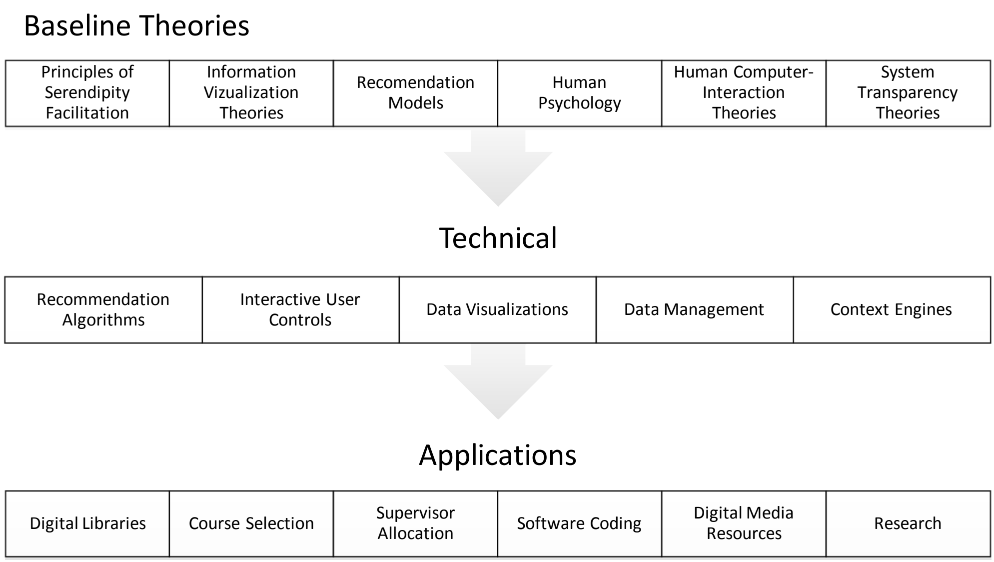

Figure 10. The development of serendipity facilitation

The development of serendipity-facilitating capabilities via the user interface of recommender systems consists of three layers (Figure 9): theoretical baselines, technologies, and applications. The baseline theories layer includes serendipity facilitation, information visualization, recommendation models, human psychology, human-computer interaction, and system transparency theories that have shaped the creation and structure of UI-facilitated serendipity of recommender system features. The technical layer shows the components that constitute the UI-facilitated serendipity recommender system. The technologies include interactive user controls such as recommendation lists, recommendation re-rank buttons, randomization sliders, and recommendation display charts. The baseline layer contributed to organizing and implementing these UI components. Finally, the applications layer represents the potential applications of such recommender systems in academia. It includes serendipitous recommendations in digital libraries, software code recommendations, degree research, and educational material.

In the studies conducted as part of this thesis, the ResQue scale was used to identify and measure serendipity within the user responses. User responses were recorded immediately after the recommender system usage on the ResQue scale (described in the Annexure). The degree to which serendipity is recognizable, the types of serendipity, and how these distinct types apply to the use of recommender systems for serendipity are further discussed in the following section. Identifying instances of serendipity would be more easily accomplished given a larger sample size of users and if the time course of the studies included serendipitous outcomes (manifestations of the serendipity process) that could be measured. Types of serendipity have been discussed by Yaqub (2018), which also provides an ample understanding of the degree to which serendipity is recognizable in research studies where information systems, in this case, recommender systems, facilitate it. As outlined by Yaqub, serendipitous experiences can be divided into four categories (Figure 11) that correspond well to the serendipity experiences and the resulting outcomes by recommender system users. Figures 11 and 12 show the types and degrees of serendipity that can be observed mostly in higher education contexts.

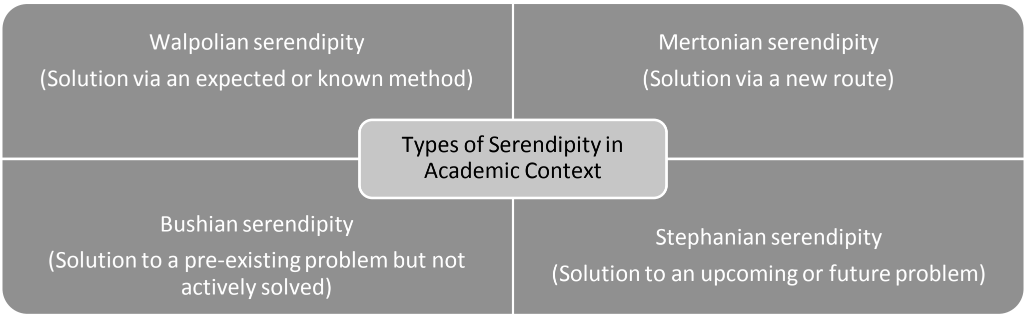

Figure 11. Types of serendipity in an academic context

Walpolian Serendipity

- The recommender system suggests an article that results in a solution in an expected set of solutions. An example of this would be user interface designers finding a user interface design that can be used to form design patterns.

- *Mertonian Serendipity*
  - The recommender system suggests an article that results in a new approach to a solution from a set of solutions (*e.g.,* a new approach to software design architecture).
- *Bushian Serendipity*
  - The recommender system suggests an article that presents a useful solution to a problem that the user was not looking for. For example, a solution to debugging software or software fault for which software developers were unsuccessful but now they have found the solution accidentally.
- *Stephanian Serendipity*
  - The recommender system suggests an article that presents a solution that might become part of a useful solution sets in the future (*e.g.,* novel topics for future research).

The serendipity of recommendations in the higher education context can lead to:

- Thesis topic selection because of the serendipitous discovery of an article
- A solution to a research problem as a part of an already selected thesis topic
- Finding future research that could extend beyond the thesis

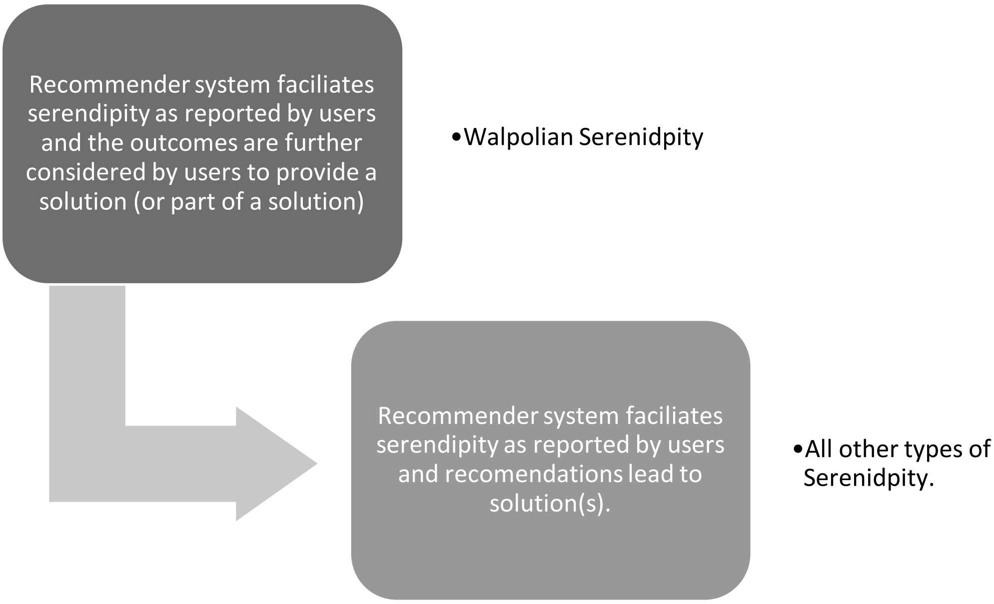

Figure 12. Degrees of serendipity observed in the academic experimental setup

3.4 Sample Size, Data Collection Protocols, Statistical Methods, and Research Ethics

The sample size and data collection protocols used have previously been described (Shani & Gunawardana, 2011). In all studies, the sample size was 25 to 60 users. The data were collected using online tools such as Google forms and saved on online platforms such as Google Cloud. The data were additionally saved locally in Microsoft Excel sheets and further analyzed on SPSS 20 statistical software. The experiments were conducted with a repeated-measures design (Within-Subject). The reason for conducting the tests repeatedly was due to the fact the experiments involved studying serendipity, therefore user feedback was collected repeatedly after a 1–2-week period. To educate users about the software, a dedicated website was maintained that discusses the history of user interfaces and their applications. The data collected were anonymized and stored on a secure online Google cloud platform with copies saved locally for data redundancy and security.

The data processing protocol is defined as follows:

- Students used the recommender systems and then immediately recorded their experience on the questionnaire
- Each student was allowed to submit only one response.
- Data were extracted from the questionnaires and data storage was conducted on cloud platforms including Google Drive and Zoho.
- The data collection was conducted with best practices for data security and privacy, including data anonymization.
- The data were measured on a Likert scale (5 – strongly disagree to 1 – strongly agree). NASA-TLX was also based on the Likert Scale.
- The datasets were organized in Microsoft Excel files and analyzed using IBM SPSS 20.
- Sentiment analyses were done by inserting comments in the set in the sentiment analysis software IntenCheck. The software generated bar charts and radar chart visualizations to visualize the sentiments of a user for a particular recommender system.

The analytical approach used is described below:

- Data were collected for users who used both baseline and advanced (developed and prototype) recommender system user interfaces.
- Discriminant analysis was used to see how the user experience improved successively.

- In addition to the discriminant analysis, statistical tests were added to measure the serendipity and user interface dynamics.
- Two studies involved a repeated measures design to measure the successive changes in a single subject over the course of the study.
- Further details are presented in the research methodology section of the thesis.
- Boxplots representing the scores assigned to each of the questions (at different time points or for the difference between time points) are presented in the summary of articles. The multivariate nonparametric spatial signed-rank test was applied to test the hypothesis that the changes introduced to the system had no impact on the vector of score medians assigned to all questions jointly. The Wilcoxon signed-rank test was used to test the hypothesis that the changes introduced to the system had no impact on each score median. 95% confidence intervals (CI) for each score median is presented. P-values <0.05 are considered statistically significant.

While the studies were conducted in Pakistan before I enrolled at Tampere University, it is noteworthy that the studies generally comply with the Finnish Guidelines on Responsible Conduct. The transparency of the research process includes providing details of the conduct of experiments and study protocols in resulting publications with anonymization of presented data. The data collected from the participants are stored in a secure online platform and details are provided in the published articles. Citations have been applied where the work of others has been mentioned. For re-printing, the articles in this thesis, special permission from the publishers has been requested. The experimental data have been submitted to Tampere University along with recommender system user interface codes.

Table 4. Overview Of Research Data and Methods

Publications	Study Type	Subjective Data			Objective Data
		Pre-Usage Expectations	Post-Usage Expectation	Comments/ Sentiment Analysis	Observation
I	Stakeholders Analysis	✓			
II	User Study		✓		✓
III	User Study		✓	✓	✓
IV	User Study		✓	✓	✓
V	User Study		✓	✓	✓
VI	Review	✓			

The publications in this thesis and the types of studies and collected data behind the publications are shown in Table 2. The studies were conducted on commercially available systems and self-developed recommender system user interfaces. The developed UI includes JabRef (Related Articles), and a book recommender developed in GraphLab. The commercially available recommender system UIs that were tested include YouTube, Amazon, Mendeley, ResearchGate, Google Scholar, and Academia. Edu.

The datasets from all four experiments show significant improvement in the serendipity users experienced utilizing the novel user interfaces developed for these. The datasets show that usefulness and surprise were significant in all experiments. Further, interface adequacy was observed in all experiments, suggesting that the user interface experience improved with the subsequent experiments with successive prototypes.

3.5 Block-Building of User Interface

The user interface development follows a block-building approach. This approach streamlines the process through sequential modifications to the software components and performance analysis.

This user interface development framework consists of three layers (Figure 10). Layer-3 defines the recommender system's core, which forms the basis of experiments done across all studies. Layer-2 defines the user interface advancements that are developed for UI-facilitated serendipity of recommendations. Layer-1 shows the evaluation and analyses that were carried out for recommender systems. Two types of recommender systems were deployed for these studies. First, baseline recommender systems, Google Scholar and basic JabRef (with recommendations list only), and then the prototypes developed for experimentation were evaluated. This framework supports a constructive experimental process by incrementally adding functions (*e.g.,* user controls and visualization modifications) to the recommender system UI.

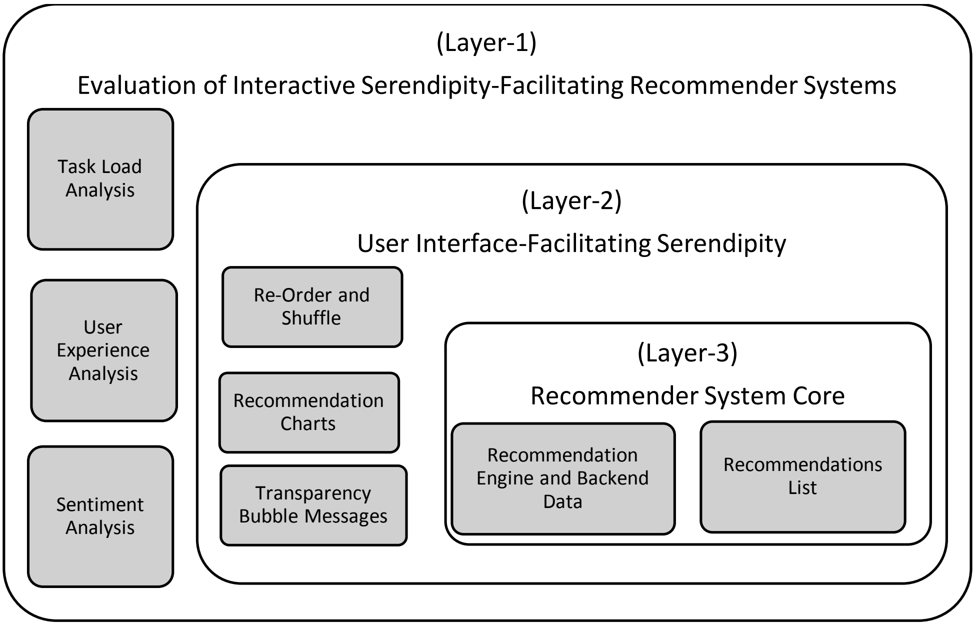

Figure 13. Block-building approach to user interface development

The research framework used places user control and visualization at the core of prototype research and development. User-centric evaluations and task load analyses were conducted for prototype recommenders and commercially available social media and e-commerce recommender systems to fully understand the user interface and the costs associated with using it. The research articles, experimentation, and narrative improved and refined over time due to the iterative process. The motivation for conducting repeated experiments was the subjective nature of serendipity, as well as limitations with recording and facilitation. Serendipity is subjective and context-dependent; if it is experienced by a user today, it might not be experienced tomorrow. Therefore, repeated measures are critical along with accompanying user sentiment analysis. This design enables us to work with real-world settings and observe phenomena in practice. Additionally, the incremental development of user interface prototypes allows for stepwise investigation of research questions as depicted in Table 3.

Table 5. Relationship among articles and research questions

Article	Publication-I	Publication-II	Publication-III	Publication-IV	Publication-V	Publication-VI
Research Questions						
RQ-1		✓	✓	✓	✓	✓
RQ-2	✓	✓	✓	✓	✓	✓
RQ-3				✓	✓	

4 SUMMARY OF ORIGINAL ARTICLES

This chapter summarizes the five published studies and one published review generated as part of this doctoral research. All the studies investigated UI-facilitated serendipity of recommendations.

The execution of the user studies required an understanding of the classroom and academic environments related to technology applications. As participants, the students and teachers needed to appreciate the benefits of this technology both for individuals as well as the larger research ecosystem. Thus, all experimental studies were thoroughly explained to the students and teachers before initiating the studies.

McCay-Peet argued that a prepared mind is important for facilitating serendipity and trigger and connection-making are key to creating a prepared mind. This thesis research aimed to foster trigger and connection-making through the development of a novel UI for recommender systems. Additionally, these experiments provided insight into how real-world users engage with technology and their perspectives on the serendipity of recommendations. This chapter introduces the recommender system UI prototypes and their respective taxonomy in each of the published studies.

4.1 Publication-I: Serendipitous Recommenders for Teachers in Higher Education

4.1.1 Research Problem

This study aimed to investigate teacher perspectives of serendipity via recommender systems. It also aimed to study the user interface design of six commercially available recommender systems. The research questions are: (a) what are current teacher experiences and perceptions of educational recommender systems concerning the user interfaces and (b) what are teacher preferences for recommender systems?

4.1.2 The Study

This study addresses teacher preference in designing a user interface for serendipity-facilitating recommendations. Six platforms were selected to investigate the research questions to conduct this study. These platforms included YouTube, Amazon, and four educational recommender systems: ResearchGate, and Academia. Edu, Google Scholar, and Mendeley. These platforms are commonly used as educational support in the higher education sector in Pakistan. Student opinions were also collected in this study. The study was critical to observing teacher preferences. Twenty teachers participated in this experiment. Since there is low literacy regarding the application of recommender systems in developing countries, only those teachers who had some previous experience with using such a platform were selected. Most teachers had Ph.D. qualifications and international publications. To evaluate both educational recommender systems, discriminant analysis was used as a statistical method to measure the difference between these recommender system user interface experiences. The user feedback data were collected in the ResQue framework standard questionnaire and analyzed using SPSS 20 software.

4.1.3 Methodological Reflections

The key strength of the UI of recommender systems is capturing user preferences for better recommender systems output. Thus, these platforms can harness the true potential of UI-facilitated serendipity of recommendations. However, there remain weaknesses in the UI designs, as evidenced by insufficient user control and a lack of education-centric serendipity. Teacher perception and knowledge of serendipity are also poor.

Among the commercially available systems evaluated, the Mendeley UI has more user control options than other recommenders' UIs. Google Scholar has a recommendation button, but other parameters are search-oriented and not recommender-specific. The user control for the Google Scholar recommender lacks further user input capabilities and low experimental participation for this platform was observed. Findings from this study support providing exposure opportunities to academic institutions to encourage the adoption and improvement of serendipity-facilitating recommender systems. There are several opportunities for enhancing serendipity facilitation through further development of these platforms. Some of these areas that can be improved include the enhancement of user controls and visualizations, greater transparency, trigger development, and enhanced connection-making for all kinds of beyond-accuracy experiences. It is also essential that teachers buy into this technology to foster adoption by students and downstream innovation and academic success as a result. It is vital to encourage teacher education regarding the theoretical framework of serendipity and both the notion and benefits of beyond-accuracy experiences. There are, however, threats to the adoption of the serendipity of recommendations. Typical accuracy orientation in courses may deter the use of serendipity. The current user interface design and lack of user controls also reduce the adoption of these technologies.

4.1.4 Key Findings and Contributions:

In addition to teacher perspectives, this study also captured student preferences. This study contributes to the understanding of UI factors influencing the implementation of serendipity-facilitating recommender systems. The teachers expressed their preferences through a questionnaire and one teacher volunteered to perform a task involving the recommender systems (YouTube and Amazon.com). This study also provides a snapshot of the higher education sector in Pakistan and the application of technology in these educational systems.

The study revealed that most teachers in the higher education sector are unaware of the recommender systems-driven process. However, some are familiar with recommender system usage in academic articles and reference management services. The study also investigates user experiences with the commercial social media website recommender systems such as YouTube and the e-commerce website Amazon for book recommendations. Overall, teachers found recommender systems promising if their use aligned with the course outlines. Therefore, it can be concluded that the serendipity feature, which involves surprising discoveries, might be perceived as not aligned with academic goals. In addition to perceptions, this study also reviews the user controls and visualization techniques used by recommender systems. This study acts as a stakeholder analysis. The study implied that the recommender system and its applications were still a new concept in this country, but the teachers and students were at least aware of recommender system capabilities. These promising findings supported the effort to design and develop novel Uis for serendipity-facilitating recommender systems. The taxonomy of the Uis studied in this article can be found in Figures 14 and 15, with labels highlighting the user controls, output (recommendation style), and transparency features.

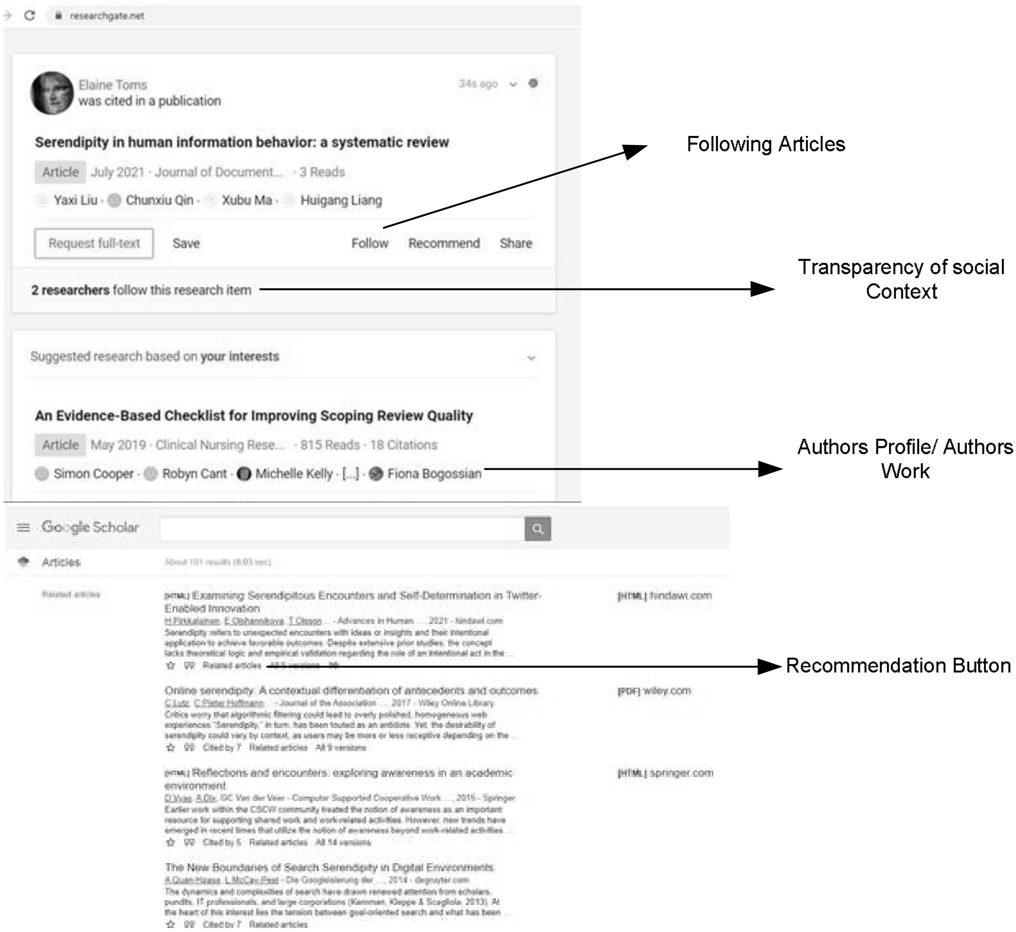

Figure 14. The recommender system user interfaces with labeled user controls (I)

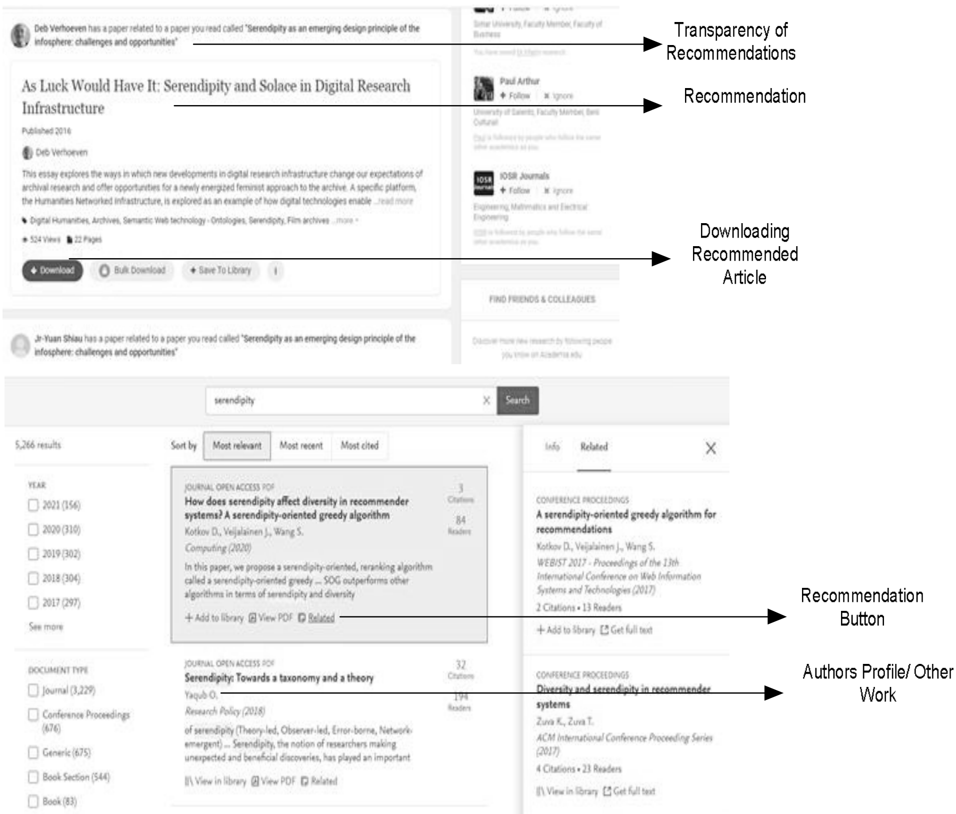

Figure 15. The recommender system user interface with labeled user control (II)

4.2 Publication-II: Transparency for Beyond-Accuracy Experience. A Novel User Interface for Article Recommender Systems

4.2.1 Research Problem:

The study included the design, development, and testing of a serendipity-facilitating user interface prototype. Further, it presented new UI design features to facilitate serendipity and improve user experiences for learners in the education/research sector. The main objectives of the research were to evaluate the use of transparency to increase trust and improve the serendipity facilitation and connection-making processes. The research questions were: (a) does transparency of recommender systems facilitate connection-making, (b) how does transparency impact user experience, and (c) how does transparency impact user trust for serendipity-facilitating recommender systems?

4.2.2 The Study

JabRef Article Recommender UI taxonomy (Mr. Dlib RAAS) and GraphLab Book Recommender UI taxonomy (MovieLens Dataset) were used in this study. The JabRef user interface is shown in Figure 16.

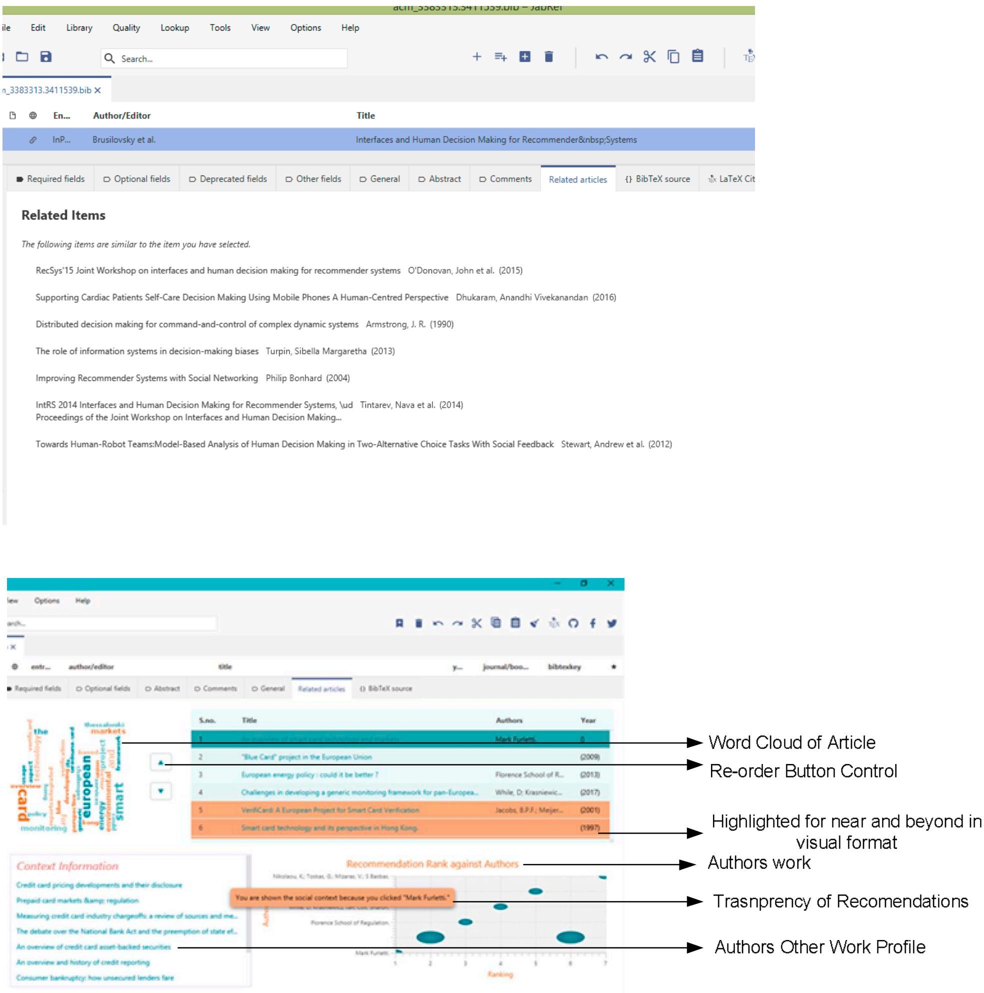

Figure 16. JabRef article recommender user interface I (upper panel) and II (lower panel)

Key features of this user interface prototype include a word cloud that helps convey central ideas about the article. This feature was added to help the user quickly grasp the themes of each article beyond the title alone. Additionally, a transparency feature was added to the UI, helping users understand recommender behavior. Each user interface section has mouse hover functionality that reveals why a specific computation has occurred. This information can work to promote reflection as well as gain user trust. The other work section provides contextual information about the other works by the same author that are available in the software. This information can be useful when the user is focused on a specific research topic.

Table 6. Experimental Details

Attribute	**Values**
Sample Size	43 users for first UI (HiFi) 60 users for second UI (Lo-fi)
Age Range	20-24 years
Users	University students
Environment	Institute of Management Sciences, Peshawar (Higher Education)
Learning Stage	Final year/BS/MS
User Interface	JabRef article recommender, GraphLab-based book recommender
Base Line	Google Scholar/JabRef
Statistical Analysis	Yes
Software	SPSS
Data Storage	Google Drive
Scale	ResQue

The students were briefed about the software and introduced to the task and user interface of Google Scholar and a prototype. The prototype was developed keeping in mind the operational environment of the institute where students access Google Scholar and other research platforms to conduct literature reviews. The prototype includes user controls to re-rank the recommendations to improve the serendipity experience. The user can also re-rank the recommendations to introduce randomness to the presented recommendations. Transparency was used to provide context for how recommended items relate to one another. This can further enhance reflective thinking and facilitate serendipity. According to McCay-Peet taxonomy, mental connection making is an essential element of serendipity. Transparency for computations and UI components are used to foster these elements. The data-centric and user-centric evaluation methods were used to evaluate the recommender systems. Student participants used both recommender systems for a specific amount of time and provided feedback through a questionnaire. The data were processed for discriminant analysis using SPSS 20 software.

Forty-three students tested one prototype while sixty students tested another. The participants were senior students with knowledge of basic research. These students were recruited from IMSciences, Pakistan, during the 2018-2019 academic year. User feedback revealed a positive experience with serendipity for research. There was a difference in user experiences between both prototype groups, which revealed that users preferred transparency for serendipity-facilitating recommender systems. Both experiments were conducted in real-life academic contexts, adding to research on the educational value of serendipity and UI design requirements to facilitate research in educational settings. The data pointed to one central theme: serendipity is valuable to the students if used and facilitated via technology. However, there remained some challenges, which are discussed in the following sections.

In addition to the statistical tests in this article, a few more tests were applied to better understand and measure the significance of the experimental results. The questionaire are presented in the annexures.

The multivariate nonparametric spatial signed-rank test was applied to test the hypothesis that the changes introduced to the system had an impact on the median of the scores assigned to each question. The median vector of the differences in the scores was significantly different from the vector zero ($p<0.001$).

Table 7. Multivariate estimate of the score median before and after, as well as the difference.

Question	Multivariate estimate of the score median
Before	(3.72, 3.35, 3.10, 2.88, 3.17, 2.90, 2.82, 2.94, 2.95)
After	(4.31, 4.38, 4.33, 4.32, 4.24, 4.18, 4.46, 4.24 4.22)
Before-After	*(-0.57, -1.02, -1.23, -1.44, -1.03, -1.29, -1.63, -1.28, -1.25)*

Table 8 presents the univariate estimates of the medians of score differences before and after and their respective 95% confidence intervals. These estimates confirm that all the median of differences varied significantly from zero, indicating that all characteristics of the system improved after the changes were implemented. Questions 4, 6, and 7 were the characteristics of the system that had the greatest impact on students' perception of improvement in the system.

Table 8. Univariate estimate of the median of differences in score before and after.

Question	Median (95% CI)	p-value
Q1	-1.0 (-1.01; -0.99)	<0.001
Q2	-1.5 (-1.51; -0.99)	<0.001
Q3	-1.5 (-2.00; -1.00)	<0.001
Q4	-2.0 (-2.10; -1.50)	<0.001
Q5	-1.5 (-2.00; -1.00)	<0.001
Q6	-2.0 (-2.00; -1.50)	<0.001
Q7	-2.0 (-2.00; -1.50)	<0.001
Q8	-1.5 (-2.00; 1.50)	<0.001
Q9	-1.5 (-2.00; -1.00)	<0.001

4.2.3 Methodological Reflections

The key contribution of this study was the design and evaluation of a novel user interface for serendipity in a specific context (*i.e.,* academic environment). This study also serves as the first step toward serendipity facilitation via novel software for faculty and student research. This study utilized JabRef, open-source software, that is already used in many parts of the world.

The Bookcrossing dataset includes all genres of books other than academic textbooks. A limitation of this study is the small number of recommendations in JabRef for reorder and uncertainty – only seven recommendations per request. If there were more than seven, it could provide the user with more randomization options and opportunities for serendipity. Additionally, because of its utility as a general-purpose machine learning framework, GraphLab requires an extensive explanation to implement transparency. This study allowed researchers to integrate more recommendations per query in JabRef for enhanced visualization and better integration than with other academic databases. However, users may struggle to navigate accurate and serendipitous recommendations. Users need to thoroughly understand the serendipity process, otherwise, students might find it confusing or ignore user controls because they do not understand their functionality.

4.2.4 Key Findings and Contributions:

This study reports on the design and evaluation of a novel user interface for recommender systems that applies re-ranking recommendations to support recommendation transparency and facilitate serendipity. The UI design includes transparency of recommendations to enhance user trust during serendipity. The user studies showed that user interfaces aid users by highlighting related and less related articles and re-ordering lists to create the effect of recommended item randomization.

This study evaluates the application of transparency in the UI for facilitating the serendipity of recommendations. This study also offers insight into the technical landscape in Pakistan, a developing country. This is important contextual information for UI design that is not found elsewhere in the literature. Further, this study contributes to the development of open-source recommender software for serendipity facilitation. The user interface was developed in Java for JabRef, an open-source reference manager. The main reason for using this software for development is that code is readily available and can be modified for future experiments or prototypes.

4.3 Publication-III: Facilitating Research Through the Serendipity of Recommendations

4.3.1 Research Problem:

The study's primary aim was to introduce and test the serendipity facilitation recommender system in a university-level academic institution in a developing country. The objectives set for the experiment were to observe serendipity facilitation on the novel user interface, observe the novelty and relevance of recommendations, and observe the usefulness of the user interface to users. The research questions are: (a) can serendipity be useful in suggesting novel and surprising items to students and (b) do interactive recommender systems that facilitate serendipity help users in research activities?

4.3.2 The Study

The user interface provides controls and visualizations for serendipity facilitation. Google Scholar was used as the baseline recommender system. As discussed in the methodology section, Google Scholar is a de facto standard platform used in educational systems in many developing countries. An institutional study was the critical methodology selected for this study. Research-level students were encouraged to use both systems. Participants included 57 students from senior university years who had research experience. Student ages ranged from 21 to 24 and they were from the Peshawar region of the K.P. (Khyber Pakhtunkhwa) province of Pakistan.

Table 9. Experimental Details

Attribute	Values
Sample Size	57 users
Age Range	20-24 years
Users	University students
Environment	Institute of Management Sciences, Peshawar (Higher Education)
Learning Stage	Final year/BS/MS
User Interface	JabRef
Base Line	JabRef baseline
Statistical Analysis	Yes
Software	SPSS
Data Storage	Google Drive
Scale	ResQue

Students interacted with both recommender systems for 10-20 minutes. During this time, the students performed the task of finding a research topic in their respective fields that they had not previously discussed with supervisors. After using the recommender systems, the students recorded their experience in the data collection forms. The data were recorded on a Likert scale. Discriminant and sentiment analyses were used to analyze the two student experiences.

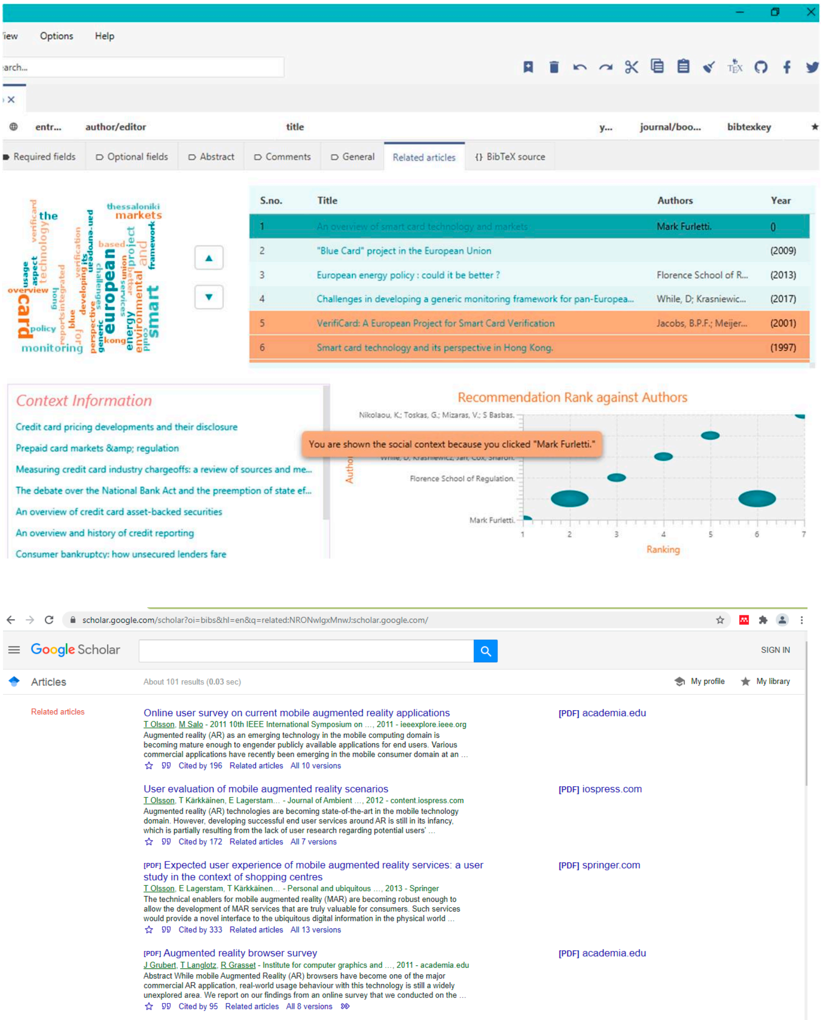

Figure 17. JabRef and Google Scholar User Interfaces

The multivariate nonparametric spatial signed-rank test was applied to test the hypothesis that the changes introduced to the system had an impact on the median of the scores assigned to each question. The median vector of the differences in the scores was significantly different from the vector zero ($p<0.001$).

Table 10. Multivariate estimate of the score median before and after, as well as the difference.

Question	Multivariate estimate of the score median
Before	(3.93, 2.57, 2.96, 3.88, 3.58, 2.93)
After	(4.46, 4.33, 3.50, 4.48, 4.35, 4.06)
Before-After	(-0.50, -1.75, -0.48, -0.60, -0.77, -1.11)

Table 11 presents the univariate estimates of the medians of score differences before and after and its 95% confidence intervals. These estimates confirm that all the median of differences differed significantly from zero indicating that all characteristics of the system improved after the changes were implemented. Questions 2 and 6 are the characteristics of the system that had the greatest impact on students' perception of improvement in the system.

Table 11. Univariate estimate of the median of differences in scores before and after.

Question	**Median (95% CI)**	**p-value**
Q1	-1 (-1; -0.99)	<0.001
Q2	-2 (-2.50; -1.99)	<0.001
Q3	-0.99 (-1.50; -0.50)	0.001
Q4	-1 (-1; -0.99)	<0.001
Q5	-1 (-1; -0.99)	<0.001
Q6	-1.60 (-2.0; -1.49)	<0.001

4.3.3 Methodological Reflections

The recommender system was perceived as valuable and trustworthy by learners (users). However, the UI-facilitated serendipity did not offer value in their current context, although learners were confident that they will consider its use for future endeavors. A few learners commented that they would like to see an on-demand peer-student research work connectivity feature added to the recommender system. A strength of this study is that it introduced user-driven processes for research and idea conception. The user control and visualization helped aid learners in navigating research with the help of recommendations, related work, and author information. In this study, there was an increased sample size as compared to the previous study. However, the study has some limitations as the number of recommendations is restricted to seven recommendations by the server — the larger the list, the higher the chance of meaningful serendipity.

4.3.4 Key Findings and Contributions:

This study generated a prototype tool for students and supervisors in the initial phases of research. The research supervisors can use this tool to foster serendipity-led innovation. This study shows that serendipity has driven research and development processes and influences teacher-student workflows. This study tested a novel user interface, increasing the number of potential recommender system applications. Students and teachers are now connected via recommendations; the social context of research is supported by the recommender system.

4.4 Publication-IV: Triggers and Connection-Making for Serendipity via the User Interface in Recommender Systems

4.4.1 Research Problem:

The primary aim of this study was to create and evaluate a user interface that triggers users for possible serendipitous encounters. To achieve this, the objectives included connecting users with various recommender items via user interface cues and helping users maintain control of serendipitous encounters. Further, this study aimed to evaluate the task-load of using a serendipity-facilitating recommender system UI. The research questions are: (a) can the user interface facilitate connection-making that contributes toward serendipity, (b) can the user interface trigger an idea that contributes toward serendipity, (c) do recommendation re-rank and transparency features facilitate serendipity, and (d) how does user interface-driven serendipity impact the user's cognitive load?

4.4.2 The Study

User interfaces used to investigate the research question were JabRef (Shuffle chart technique along with re-rank) and Google Scholar (as a baseline). The key changes to this UI are the introduction of a shuffle chart, transparency of recommendations, and keyword articles. The study type was an institutional study. The study focuses on the Pakistani educational environment, understanding and introducing research recommendations to 40 degree-seeking students. Since the study involved measuring serendipity, a repeated-measure design along with sentiment analyses were used. The critical statistical method used was discriminant analysis. The ResQue standard questionnaire was used to collect data for subjective analyses and the NASA-TLX was used to measure the cognitive load.

Table 12. Experimental details:

Attribute	Values
Sample Size	40 users
Age Range	20-24 years
Users and Environment	Institute of Management Sciences, Peshawar
Learning Stage	Final year/BS/MS
User Interface	JabRef
Base Line	Google Scholar/JabRef Serendipity facilitating
Statistical Analysis Software	SPSS
Data Storage	Google Drive
Scale	ResQue, NASA-TLX

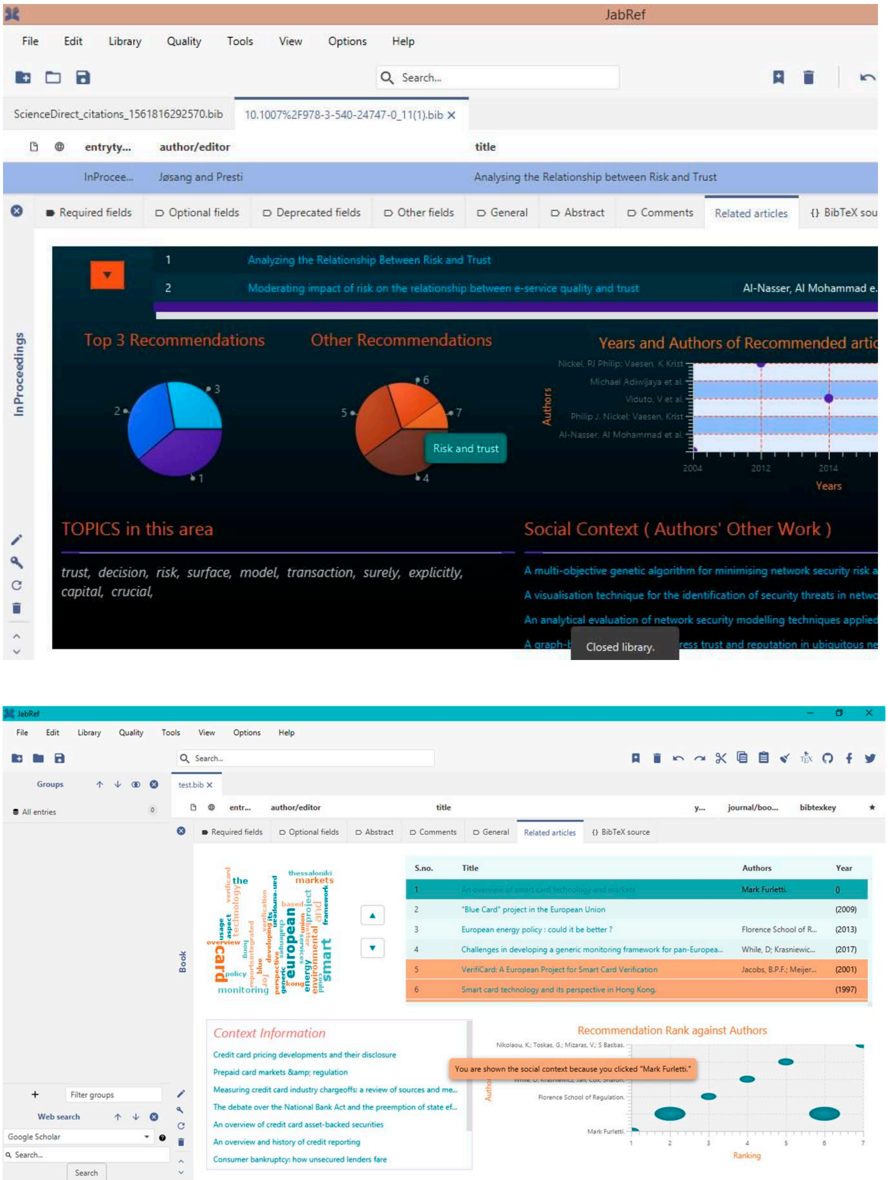

Figure 18. JabRef-1 (upper panel) and JabRef-2 (lower panel) user interfaces

For the first read, the statistical analysis is as follows. The multivariate nonparametric spatial signed-rank test was applied to test the hypothesis that the changes introduced to the system had an impact on the median of the scores assigned to each question. The median vector of the differences in the scores was significantly different from the vector zero ($p<0.001$).

Table 13. Multivariate estimate of the score median before and after, as well as the difference.

Question	**Multivariate estimate of the score median**
Before	(3.72, 3.35, 3.10, 2.88, 3.17, 2.90, 2.82, 2.94, 2.95)
After	(4.31, 4.38, 4.33, 4.32, 4.24, 4.18, 4.46, 4.24 4.22)
Before-After	*(-0.57, -1.02, -1.23, -1.44, -1.03, -1.29, -1.63, -1.28, -1.25)*

Table 14 presents the univariate estimates of the medians of score differences before and after and its 95% confidence intervals. These estimates confirm that all the median of differences differed significantly from zero indicating that all characteristics of the system improved after the changes were implemented. Questions 4, 6, and 7 are the characteristics of the system with the greatest impact on students' perception of improvement in the system.

Table 14. Univariate estimate of the median of differences in scores before and after.

Question	**Median (95% CI)**	**p-value**
Q1	-1.0 (-1.01; -0.99)	<0.001
Q2	-1.5 (-1.51; -0.99)	<0.001
Q3	-1.5 (-2.00; -1.00)	<0.001
Q4	-2.0 (-2.10; -1.50)	<0.001
Q5	-1.5 (-2.00; -1.00)	<0.001
Q6	-2.0 (-2.00; -1.50)	<0.001
Q7	-2.0 (-2.00; -1.50)	<0.001
Q8	-1.5 (-2.00; 1.50)	<0.001
Q9	-1.5 (-2.00; -1.00)	<0.001

For the second read, the statistical analysis is as follows. The multivariate nonparametric spatial signed-rank test was applied to test the hypothesis that the changes introduced to the system had an impact on the median of the scores assigned to each question. The median vector of the differences in the scores was significantly different from the vector zero (Table 1, p<0.001). In this case, all the components of the multivariate estimate of the median of the difference in scores are negative indicating that the shift in the center of the distribution is to greater values of the scores after the changes were implemented in the interface.

Table 15. Multivariate estimate of the score median before and after, as well as the difference.

Question	Multivariate estimate of the score median
Before	(3.92, 3.75, 3.31, 2.76, 3.16, 3.54, 3.22, 3.47, 3.27, 3.42, 3.60)
After	(4.13, 3.94, 4.06, 4.00, 3.46, 4.22, 3.63, 3.53, 4.00, 3.80, 4.09)
Before-After	*(-0.18, -0.17, -0.79, -1.24, -0.29, -0.68, -0.40, -0.04, -0.72, -0.38, -0.48)*

Table 16 presents the univariate estimates of the medians of score differences before and after and its 95% confidence intervals. These estimates confirm that for all questions except 2, 5, and 8, the medians of the differences are negative and differed significantly from zero indicating that the changes introduced in the system had a positive impact on students' perception. Questions 2, 5, and 9, corresponding to "relevance to my activities", "significant difference from each other" and "help in understanding why items are recommended" are the characteristics of the system with no change in students' perception.

Table 16. Univariate estimate of the median of differences in scores before and after.

Question	Median (95% CI)	p-value
Q1	-1.0 (-1.01; 0.00)	0.049
Q2	-0.5 (-1.00; 0.00)	0.215
Q3	-1.0 (-1.50; -0.99)	<0.001
Q4	-1.5 (-2.00; -1.00)	<0.001
Q5	-0.5 (-1.00; 0.00)	0.182
Q6	-1.0 (-1.5; -0.99)	0.002

Q7	-1.0 (-1.01; 0.00)	0.006
Q8	0.0 (-1.00; 0.50)	0.784
Q9	-1.0 (-1.50; -0.99)	<0.001
Q10	-1.0 (-1.01; 0.00)	0.034
Q11	-1.0 (-2.00; -0.50)	0.012

Task load

For the first read, the hypothesis of Normal Multivariate Distribution of the scores was rejected (p<0.001). In consequence, MANOVA cannot be applied to analyze these data. The multivariate nonparametric spatial signed rank test was applied to test the hypothesis that the changes introduced to the system had an impact on the median of the scores assigned to each question. The median vector of the differences in the scores was significantly different from the vector zero (Table 1, p=0.008). In this case, all components of the multivariate median estimate of the difference in scores are, except the corresponding to question 4, negative indicating that the shift in the center of the distribution is to greater values of the scores after the changes were implemented in the interface.

Table 17. Multivariate estimate of the score median before, after and its difference.

Question	Multivariate estimate of the score median
Before	(10.66, 9.63, 11.03, 9.99, 8.68, 6.68)
After	(11.43, 10.91, 11.69, 10.07, 12.03, 10.86)
Before-After	(-0.44, -0.84, -0.14, 1.31, -2.84, -3.70)

Table 2 presents the univariate estimates of the medians of score differences before and after and its 95% confidence intervals. These estimates along with p-values confirm that for questions 1, 2, 3 and 4 the medians of differences are not significant while for questions 5 and 6 are positive and differed significantly from zero. This means that task load associated with “mental”, “physical” and “temporal” demand and “performance” did not change between user interfaces 0 and 1 while there was an increment in effort and frustration. The median of the scores assigned to effort was 4.9 points greater after the changes were introduced to the software than before they were made. With 95% confidence, this increment can be between 1 and 7 points greater. The median of the scores assigned to frustration was 5.0 points greater after the changes were introduced to the software than before they were made. With 95% confidence, this increment can be between 2 and 8 points greater.

Table 18. Univariate estimate of the median of differences in score before and after.

Question	Median (95% CI)	p-value
Q1	-0.5 (-3.50; 1.50)	0.768
Q2	-0.5 (-3.50; 1.50)	0.361
Q3	0.0 (-2.00; 2.00)	0.846
Q4	1.5 (-1.00; 4.00)	0.175
Q5	-4.9 (-7.00; -1.00)	0.006
Q6	-5.0 (-8.00; -2.00)	0.002

For the second read, the hypothesis of Normal Multivariate Distribution of the scores was rejected ($p<0.05$). In consequence, MANOVA cannot be applied to analyze these data. The median vector of the differences in the scores was significantly different from the vector zero (Table 3, $p=0.005$). In this case, all the components of the multivariate estimate of the median of the difference in scores are positive indicating that the shift in the center of the distribution is to smaller values of the scores after the changes were implemented in the interface.

Table 19. Multivariate estimate of the score median before, after and its difference.

Question	Multivariate estimate of the score median
Before	(10.83, 10.45, 11.25, 10.18, 12.07, 11.14)
After	(8.56, 8.07, 8.78, 8.30, 8.95, 7.51)
Before-After	(2.10, 2.28, 2.31, 1.67, 2.74, 3.23)

Table 4 presents the univariate estimates of the medians of score differences before and after and its 95% confidence intervals. These estimates along with p-values confirm that for all questions except 4, the medians of differences are positive and differed significantly from zero. This means there was a reduction in task load associated with "mental", "physical" and "temporal" demand, effort and frustration but not associated with performance between user interfaces 0 and 1. The aspect with greater reduction in task load was frustration. The median of the scores assigned to frustration was 4.0 points smaller after the changes were introduced to the software than before they were made. With 95% confidence, this reduction can be between 2 and 6 points smaller. The median of the scores assigned to effort was 3.0 points smaller after the changes were introduced to the software than before they were made. With 95% confidence, this reduction can be between 1.5 and 5 points smaller.

Table 20. Univariate Estimate of the Median Of Differences In Score Before And After.

Question	Median (95% CI)	p-value
Q1	2.0 (0.50; 4.00)	0.008
Q2	2.5 (1.00; 4.00)	0.003
Q3	2.5 (1.00; 4.50)	0.004
Q4	2.0 (-0.50; 4.00)	0.141
Q5	3.0 (1.50; 5.00)	0.001
Q6	4.0 (2.00; 6.00)	<0.001

4.4.3 Methodological Reflections

This is the first study of task load and serendipity-facilitating recommender system along with the JabRef-1-related work. User studies are conducted in a real-world context. The recommendation randomization was done via the novel shuffle and re-rank buttons introduced in this study. The re-rank was also complemented with the shuffle of recommendations charts. Contextual factors (*e.g.,* academic setting) were taken into consideration during the experiment. A weakness of the study is the sample size. More student responses could provide a more detailed understanding and statistical significance. Additionally, there remains a need to test the software in diverse experiential environments, such as for doctoral students and various examination and assignment formats and fields. Furthermore, more recommendations from the backend server are crucial as more shuffles and re-ranking allow for more serendipity. Finally, the experiment was conducted for a limited time. Repeated experiments and longer durations can help to better understand the contextual requirements of the academic environment.

More extensive and specialized task load analyses will offer valuable information about the user interface cognitive load. Sentiment analyses can also be improved with interviews and automated natural language processing. However, some key challenges might risk or hamper understanding the trigger and connection-making processes. Serendipity is a process where a new route is adopted that might create disorganization for the student to select a particular article. Furthermore, students with diverse backgrounds and at multiple academic stages are needed to introduce serendipity-facilitating recommender systems into the mainstream higher education system.

4.4.4 Key Findings and Contributions:

The UI-design process enabled a better user experience by providing an author's related work, enhancing transparency, and allowing for recommendation re-rank and shuffle controls. The results report significance in task load due to the increasing complexity of user controls for serendipity facilitation, indicating a significance on a user's mental workload. The users also demanded more recommendation items per request for a better serendipity experience. This study provides further insight into the impact of recommender system technologies in academic settings. In this study, both user interfaces of the same recommender systems source were used. The study also contributed to the understanding and applying user controls and visualization techniques for serendipity-facilitation. Second, the detailed study of the user interface for serendipity-facilitating recommender systems is discussed. This study shows that a user interface can be designed to trigger a prepared user for connection-making for a serendipitous experience. User interface components such as buttons, re-ranking, and shuffle charts were used for facilitating serendipity.

4.5 Publication-V: NASA-TLX Based Workload Assessment for Academic Resource Recommender System

4.5.1 Research Problem:

The main aim of this study is to investigate the cognitive workload of commercially available recommender systems in an academic system. Studying these recommender system user interfaces can help us understand how future recommender systems can incorporate serendipity-facilitation capabilities in user interfaces and their ultimate adoption in educational systems. The research questions are: (a) what are serendipity trends in educational recommender systems and (b) what are the cognitive workload trends in educational recommender systems?

4.5.2 The Study

This study involves four recommender systems. The recommender systems used to study task load are Google Scholar-related articles, Mendeley recommendations, ResearchGate-related articles, and Academia.Edu, as seen in Figure 19. Key features of the user interface are user controls, recommendation presentations, and over-user interface design. The recommender systems provided less user control to the users in manipulating the recommendations list as compared to Google Scholar. Most of the recommendations were provided in a top-N list fashion. The recommender systems under study are algorithmic driven accuracy-oriented systems. The users experienced a low level of control on recommendation processes and a ma moderate level of mental and perceptual activity.

Table 21. Experimental Details:

Attribute	**Values**
Sample Size	17 users
Age Range	18- 25 years
Users	University students
Environment	Institute of Management Sciences, Peshawar (Higher Education)
Learning Stage	Final year/BS/MS
User Interface	ResearchGate, Mendeley, Google Scholar, Academia.edu
Repeated Measures	Yes
Statistical Analysis Software	SPSS
Data Storage	Google Drive
Scale	ResQue, NASA-TLX

Seventeen responses were considered for sentiment analyses. The sentiments were recorded on the digital cloud platform (Google Drive and Zoho Drive) and fed into the sentiment analysis software. SPSS 20 was used to analyze quantitative data responses. The sentiment analysis software picked a range that indicates a particular experience of the user, from feedback data received from them in the comments.

Wilcoxon tests and Kruskal Wallis Tests were conducted to quantify and statistically evaluate user responses. Furthermore, discriminant analyses were conducted to appreciate the overall user experience.

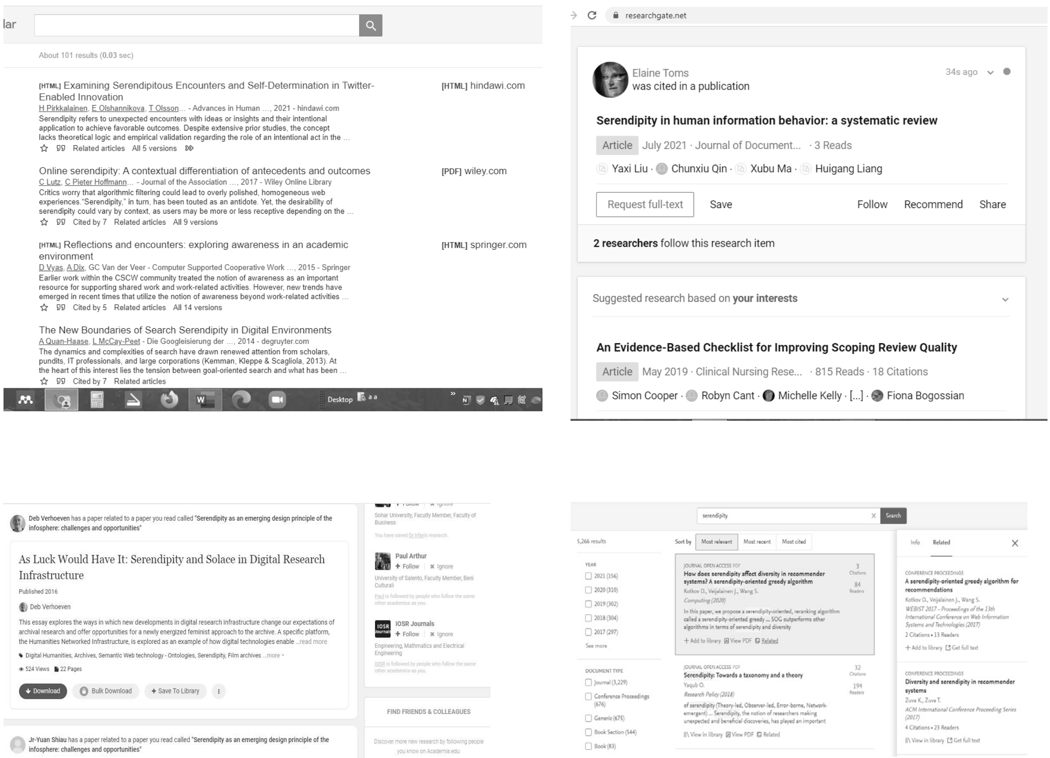

Figure 19. Google Scholar, ResearchGate, Academia. Edu, and Mendeley User Interfaces

4.5.3 Methodological Reflections

Recommender systems with an accuracy-centric design of recommendations leverage fewer user controls to manipulate recommendations. Therefore, the recommendation UI has a negligible cognitive load on the users. Search trails and navigation can improve these accuracy-centric recommender systems. The accuracy-centric recommender system UI lacks visualization-based navigation support for users to explore the recommendations.

There are many opportunities to improve the recommender system user interface design. A larger sample size and more diverse participant cohort could demonstrate how users' cognitive load influences the implantation and usage aspect of academic recommender systems. The cognitive load of recommender user interfaces increases with complexity. These findings can be used to design serendipity-facilitating recommender systems for academics.

4.5.4 Key Findings and Contributions:

Google Scholar has the most user controls followed by Mendeley, Academia.Edu, and ResearchGate. This study reports a diverse task load associated with the recommender system UIs used in academia. While these UIs are not designed to facilitate the serendipity of recommendations, there are instances where users report serendipity experiences. The study also found that task load influences user performance.

This study has two key aspects. First, it reveals considerations for a user interface design for educational recommender systems concerning the cognitive load for users. Most of the recommender systems currently available focus solely on advancing recommendation methodologies. As major educational recommender systems adopt serendipity-facilitation features, cognitive load analyses will be increasingly important. Second, this study conducted cognitive load analyses for user interface-facilitated serendipity. This study is the first to evaluate the cognitive load of educational recommender systems. Modifications that could be made include the introduction of additional user controls and visualizations for serendipity facilitation. Task load and serendipity are likely context-dependent and will vary around the world. This study serves as a serendipity and task load analysis in educational environments in a developing country, a novel perspective not found elsewhere in the literature.

4.6 Publication-VI: Review of User Interface-Facilitated Serendipity

4.6.1 Research Problem:

Publication VI is a literature review related to serendipity-facilitating user interfaces and recommender systems. The key objectives for the review included understanding the emergence and importance of the UI in recommender systems. The review also focused on identifying key user interface approaches for the facilitation of serendipity in recommender systems. The research question addressed in this review was: what kinds of interactivity approaches are available to facilitate serendipity in recommender systems?

4.6.2 The Study

The study presented an overview of serendipity and recommender systems, including a detailed overview of user interfaces in recommender systems. The review mainly focused on information system and recommender system studies that report user interface design factors that are critical in facilitating serendipity. This study discussed the serendipity-facilitating UI user controls and visualization functionalities. Experimental details and evaluation criteria are included.

4.6.3 Methodological Reflections

This review provides a foundation for advancing the interactivity and serendipity in recommender systems. The reviewed articles are from various sectors and contexts, but they can be used to inform the design and implementation of recommender systems for the higher education sector. This review contributes a systematic summary and discussion of recent advancements in interactive recommender systems and how user controls and visualizations have been critical in facilitating serendipity. It also identifies weaknesses with current published studies in terms of sample size, experimental conditions, and the relatively small number of applications for serendipity-facilitation that have been studied in real-world contexts. The review reveals a substantial number of opportunities for future studies to investigate interactive recommender systems for serendipity. Specifically, there is significant potential for serendipity-facilitating recommender systems to aid in scientific discoveries through effective user interface designs. Additionally, the recommender system algorithmic advancements can be further realized via UI designs that move the work-bound algorithm beyond accuracy.

5 DISCUSSION AND CONCLUSIONS

This chapter concludes and describes future research directions for facilitating serendipity with the help of interactive recommender systems.

5.1 Key Findings

> *RQ1. What kinds of User Interface (UI) solutions of recommender systems can be used to facilitate serendipitous discoveries of a learner?*

The user studies conducted as part of this research shows how the user interface can facilitate serendipity and be useful to learners in the higher education sector. Publication-I supports the notion that there is room for study and improvement of UIs for recommender systems for academic use. Current UIs are not designed to facilitate serendipity. In publications II, III, and IV, the user studies show that user controls and visualizations implemented in software prototypes can collectively facilitate the serendipity of recommendations. Recommender system transparency and post recommendation manipulation techniques (*e.g.,* recommendations re-rank and shuffle features) along with publication years and author information charts were evaluated in these studies. Three different prototype UIs were developed to achieve this objective. UI components can help trigger a prepared user and foster connect-making among novel items and ideas to facilitate the serendipity experience. The UI components include user controls that can shuffle and re-order the recommendations list. Further, the pie charts for recommendations displayed along with the grid-based list view are instrumental in serendipity facilitating UI. The UI also includes articles authors list timeline and research publications list. Therefore, UIs were tested over time and have demonstrated that UI solutions can be used to facilitate the serendipity of recommendations. The benefits of UI design-based solutions are that the UI-driven approach offers an alternative to the algorithmic way for users to experience serendipity. Further, UI-based solutions can be instrumental in establishing trust among the users (learners). This trust is critical when UI facilitates serendipity. It's the reason that serendipity facilitation is a new approach to academic research. User trust is important in introducing serendipity facilitating information systems (recommender systems). However, there are limitations to this approach. The UI-based approach increases user's (higher education learner) task load. Additionally, the access and exposure of academic users in Pakistan to recommender system applications is limited, which caused practical challenges to participant recruitment and implementation of user studies.

McCay-Peet's (2015) taxonomy of serendipity is extended to designing user interfaces for facilitating serendipity. The concept of trigger and connection-making is operationalized by the transparency of recommendations and user controls for post-recommendations randomization. Trigger and connection-making are facilitated by the UI design. In all user studies, while evaluating the user experience of learners, the learners experienced diversity, usefulness, and novelty of recommendations. Therefore, UI-facilitated serendipity is a solution for the beyond-accuracy experience for recommender systems designs.

RQ2. How does UI-facilitated serendipity in recommender systems advance the objectives of higher education?

The user study in publication-I shows that recommender system applications are novel in the academic system in Pakistan. The main exposure of these users (teachers and students) to recommender systems is with commercial and social media recommender systems. The recommender systems embedded in academic software, such as reference management software, are also common recommender system platforms utilized by users (students and teachers).

Publications II, III, and IV indicate positive user experiences provided by UI-facilitated serendipity in the recommender system in the educational process. Benefits include article selection, new topic selection for presentations or research theses, positioning research in the context of an author's related work and increasing diversity in related work. Publication III focused on the academic research task of conducting a literature review for a final thesis or project). The study reported that the higher education research process could be supported by recommender system applications. More user studies with larger sample size and over an extended duration will help us better understand how UI designs can be adapted to better facilitate serendipity in recommender systems.

Article recommender systems can have a positive impact on students' research processes in higher education. Teachers and students can leverage recommender systems' capabilities to better navigate and search for a solution when conducting a literature review. Recommender systems can also advance the teacher's role in supervising research students by applying a recommender system when searching relevant literature, therefore lessening the burden on teachers.

One critical aspect of ensuring the success of UI-facilitated serendipity of recommendations is continued user exposure and stakeholder maturity. There is still a need to understand and communicate with stakeholders in the higher education context (*e.g.,* students, researchers, instructors) to convey the potential and application of serendipity of recommendation for innovation and facilitation of research. User-centric evaluations and larger sample sizes will improve the research needed to inform UI design and various platform exposures to improve stakeholders' perceptions. Higher education, and the industry, in general, must appreciate serendipity as an accident with capability. Further research is needed to better understand the current perspective on serendipity. To advance the utility of serendipity, the stakeholders must first be educated on when and how to use it. It is essential to mention that serendipity is rare, and thus the recommender system cannot provide a serendipitous result each time. Managing user expectations is essential.

The users' sentiments focused on themes such as user interface design issues like layout and color selection. It also included user controls and interface components. Furthermore, it also included a recommendations list and users' requirements to integrate more functions.

JabRef and Google Scholar were the recommender systems that received many users' comments and formed the basis of sentiment analysis insights. For Google Scholar, there was a demand for charts and visualizations for better information presentation. The information presentation required was the support of graphics to avoid information clutter. However, the extensive list of recommendations in google scholar was the decisive point. For JabRef, the users believed it was easier to understand as a rich graphical user interface supported it. However, the designs of JabRef received comments improving user interface color and demand for more recommendations in the recommendation lists. The detailed sentiment analysis report is presented in the article's annexures.

There were numerous challenges in conducting this research in the Pakistani academic environment. These challenges include differences between Pakistani and Finnish academic settings as well as unanticipated obstacles in conducting this research.

1- Differences between the Pakistani and Finnish academic research settings

Much published research has been conducted in the context of developed countries, such as those in Europe. The differences between European, specifically Finnish, and Pakistani research contexts are multifaceted and include differences in education systems, information communication technology (ICT) literacy, student demographics, and technological exposure. Additionally, perceptions about serendipity and its applications differ between these two settings. These factors are discussed in more detail below:

- Education system differences
    - Pakistan is a developing country with a large population and an emerging economy. This underscores the opportunity that remains for the improvement of the ICT infrastructure. There is an opportunity for researchers to innovate new products for academia, though this opportunity comes with a great challenge as ICT-based transitions are time-consuming and difficult. Finland's education system is world-class; the latest tools and technologies are in place to support student learning. Therefore, there is a contrast in the student learning experience in Pakistan compared to Finland (or Europe).
- ICT literacy
    - Information communication technology (ICT)-based literacy is directly proportional to the country's socio-financial status and overall growth. Pakistan's ICT literacy is still in its infancy. Due to inflation and higher prices of electronic devices (e.g., smartphones, tablets, laptops), the ICT literacy and experience related to it are different in Pakistan compared to Finland (Europe).
- Software exposure and demographic differences in higher education
    - In Pakistan, most students in the higher education sector are undergraduate and master's level students; there are very few students at the doctoral level.-Many students involved in the user studies reported in this thesis were educated about serendipity and familiar with recommender system-based research.
    - Few Pakistani students have exposure to European software tools and standards applied in doctoral and research practices. Therefore, exposure to research tools and practices is one of the critical factors

in the differences between Pakistan and European (Finland) research practices.

- Perceptions about serendipity and its application
    - Educating users about serendipity in the higher education sector in Pakistan (students and teachers) is challenging. Though the concept of serendipity is relatable in their daily life, the application of this concept to computational systems examples was far more challenging. Using the familiar example of serendipity experience in daily life is a way to introduce users to how such a concept could be used if implemented computationally in information systems.

2- Unexpected obstacles

In addition to the challenges outlined above, there were unexpected obstacles encountered while conducting this research. These obstacles include user participation, teacher and student perspectives, and data collection challenges. These challenges are outlined in more detail below:

- User participation and teacher perspectives
    - The teachers were skeptical about whether this system would benefit the academic system. There was reluctance to transition from the current search-based processes.
    - Surprisingly, students were more positive than teachers about the outlook and application of serendipity-facilitating recommender systems.
- Student perspectives
    - Students related their serendipity experience to those utilized by YouTube and other social media platform recommender systems. Further, they were familiar with academic platforms such as ResearchGate, Google Scholar, and Mendeley where they experienced serendipity when using these recommender systems.

However, there was no concrete example of how serendipity could be experienced in their academic life via digital platforms.

- Data collection and uncertainties
    - Collecting data during a classroom session and after class using recommender systems was challenging. Student users very courteously gave their time to use the recommender systems and provide valuable feedback. However, many students did not participate in the research study. Had they participated, a much larger, more powerful dataset would have been available for analysis.

RQ3. What is the task load (i.e., the difficulty a user experiences when attempting a task) of UI-facilitated serendipity of recommendation on learners?

Publications III, IV, and V show the task load associated with recommender systems. The research also discussed the task load associated specifically with the serendipity UI. When task load was studied among the serendipity facilitating UIs, the studies showed that task load increased. There was no substantial task load increase in the recommender systems where user controls were not applied to facilitate serendipity. Similarly, when task load was studied for the academic recommender system user interfaces, the studies showed no substantial task load, but there were variations among the recommender systems. Google Scholar has the most user controls, followed by Mendeley, Academia. Edu, and ResearchGate. Users experienced low control and a moderate level of mental and perceptual activity. Implications of UI design and serendipity on task load will depend on how prepared a user is when applying user controls on recommender systems, as well as user controls for facilitating serendipity in these systems.

Task load of recommender systems is a challenge when deploying them to academic research settings. Higher task load on users when using a UI-facilitated serendipitous recommender system will negatively affect the applications in higher educational research settings. Further, the commercially available research article recommender systems user interfaces also need to be reviewed for their associated task loads. Best practices can be adopted from several studies in similar academic research settings and user (students and teachers) preferences.

The experiments conducted during this doctoral research serve as proof-of-concept studies that pave a new direction for serendipity facilitated by a recommender system. Nevertheless, experimental challenges remain. The user interface-facilitated serendipity of recommendations has a long way to go to meet user (students and teachers) needs. Additionally, there are different types of serendipity and the UI must be adapted to accommodate multiple varieties of serendipity experiences.

5.2 Overall Discussion

The key strength of this work is UI prototypes as a start point for UI-based serendipity facilitation in recommender systems research. This work advocates and provides a starting point for serendipity-driven learning and research for higher education institutions. Further, this work also presents an open-source software modification and novel user interface design development.

There are, however, a few methodological limitations regarding this research. First, the dataset is small due to constraints in the selection of participants (users/learners). Not many final-year students were available to experience the recommender system in their research work. Second, the duration of experiments was limited due to competing commitments for these students. Third, the recommender systems had limited recommendations generated per request, therefore limiting recommendation randomizations at the user interface level. These methodological limitations suggest that to advance the current state of work, better research approaches must be adopted. These approaches involve first developing a web-based recommender system and user accompanying interface with rich user controls. Second, the experiments require additional time so that there is a more comprehensive understanding of serendipity and potential outcomes in the academic systems studied.

User interfaces of other accuracy-oriented recommender systems – like radar charts – can be leveraged to advance serendipity. A better understanding of user needs is required to present the serendipity of recommendations to a broader academic audience. Though randomization has been evaluated in these studies, it is not the only solution to facilitate the user control-based serendipity experience. Transparency and context of recommendations are two promising candidates for future designs to support triggers and connection-making functions as well as context-aware computing. Serendipity has great potential for both users and stakeholders in academic settings with multiple applications such as library book recommendations, research advancement, and course planning.

Moving beyond the traditional academic search-based process can be challenging. Contextual data are critical in leveraging serendipity, aided by user interface elements such as explanations of recommendations. There is a sea of articles that context-aware applications can filter through. Therefore, in addition to UI, advancing context-awareness may help add new capabilities to implementing serendipity.

There are several contexts for the serendipity of recommendations in academia, such as student research supervision, where recommender systems have been developed. Serendipity can help students and teachers find innovative ideas for projects and thesis topics. Student course recommenders are another example that is currently in use. Serendipity can further enhance the course allocation by recommending courses to users based on their final project or research topic. Intra-subject recommendations can be achieved by recommending serendipitous content to students that can further be used for course presentations, assignments, and projects. The serendipity concept may bring diversity and novelty to each student's work.

The data collected from user interface evaluations shows that the user interface facilitated serendipity but also improved the overall user experience. There was no substantial evidence that evaluations (ResQue subscales) negatively affected the overall experiment. However, a long-term study is required to fully understand these effects. There is still more research needed to understand students' preferences when it comes to user interface design for serendipity-facilitating recommender systems. We also conducted sentiment analyses and ResQue-based evaluations that enhanced our understanding. Our analyses revealed that there is a more significant task load with the serendipity-enhancing interface for recommender systems, due, at least in part, to the increased number of controls. The increased number of controls is necessary as these add more functions to the user interface that facilitate serendipity, whereas a strictly algorithmic approach would not require added controls.

Key conclusions from this research are as follows:

1. We can facilitate serendipity via the user interface. Serendipity facilitation via the user interface of recommender systems is still in its infancy and requires more prototype development and user studies with larger sample sizes and more considerable periods.
2. The process of trigger and connection making can be achieved via the user interface for the recommender system to facilitate serendipity. More studies are required to understand different user interface components and controls, their interaction with the user, and how they impact user experience. For this purpose, objective data can be critical to understanding user controls and visualizations when serendipity facilitation is the aim of these components.
3. ResQue was instrumental in measuring serendipity. This is consistent with the literature that shows that ResQue has been instrumental in capturing serendipity and user interface dynamics. ResQue includes enough questions to capture serendipity as well as how recommendations and user interface components, such as transparency and controllability of user interface, contribute to serendipity.
4. Higher education institutions need new research support tools, especially in developing countries. There is a specific need for recommender systems and serendipity utility awareness. The understanding of serendipity in the local context is essential. Otherwise, such tools are difficult to test.

5. The artificial intelligence-driven process should be introduced and tested along with search-based techniques. The user studies revealed that current research practices in the higher education sector in Pakistan are search-based. The students and teachers are aware of artificial intelligence, but serendipity facilitating recommender systems could provide a starting point in introducing such systems.
6. Recommender systems can be instrumental in serendipity facilitation and leveraging it in the educational process. However, the current technology and user awareness status show that a considerable amount of human and technological efforts are required to make such a system mainstream and realize its benefits.

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APPENDIXES

Appendix A

List of Items

1- Questionnaire
2- Pairwise test results

Publication-II Questions

- Q1-The recommendations are **useful** for me
- Q2-The items recommended to me match my **interests**
- Q3-The recommendations provide me with **novel** information
- Q4-The recommendations are **surprising** to me
- Q5-The recommender can be **trusted**
- Q6-The recommender interface provides **sufficient information**
- Q7-The system **helps me understand** why items were recommended to me
- Q8-I was able to **take advantage** of the recommender very quickly
- Q9-I **feel in control** of telling the recommender

Note: The dependent variables are highlighted in **bold**

Likert Scale:

Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree

Pairwise Tests

Figure A1 shows boxplots of the scores assigned to each of the nine questions before and after the changes were implemented in the system. The shifts in the boxplots towards larger values after the changes were implemented would indicate a positive impact on students' opinions of these changes. Figure A2 shows boxplots of the differences in the scores assigned to each of the nine questions before and after the changes (before – after). In this case, question 7 represents the characteristic of the system with the greatest impact on students' perception of improvement in the system.

Figure A1. Boxplots of scores assigned to each question before and after the changes to the system.

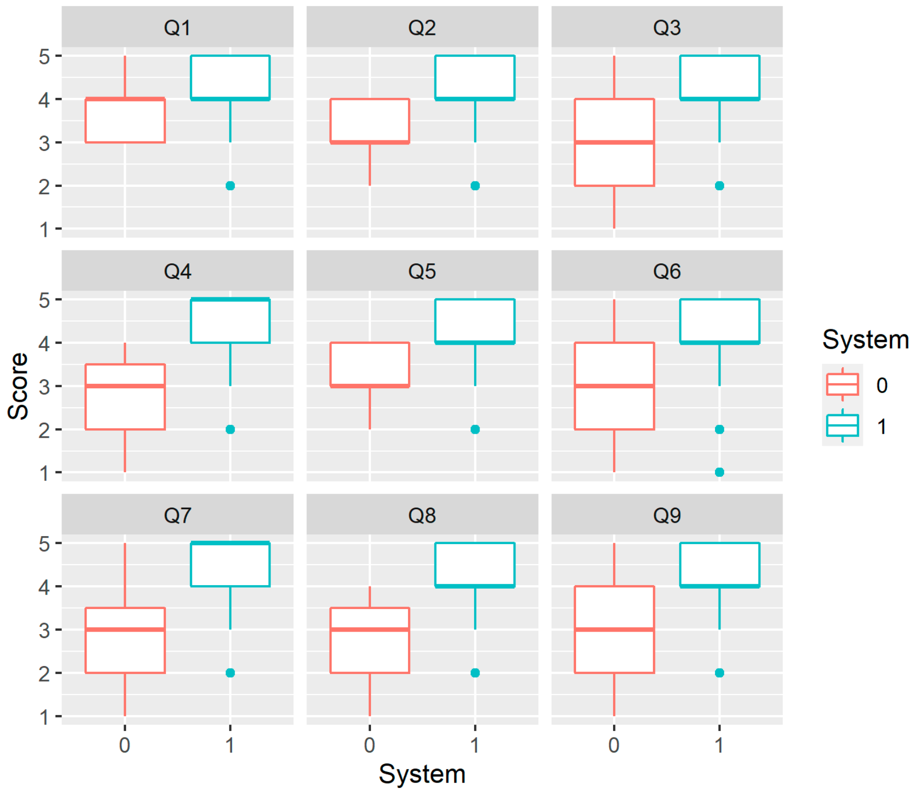
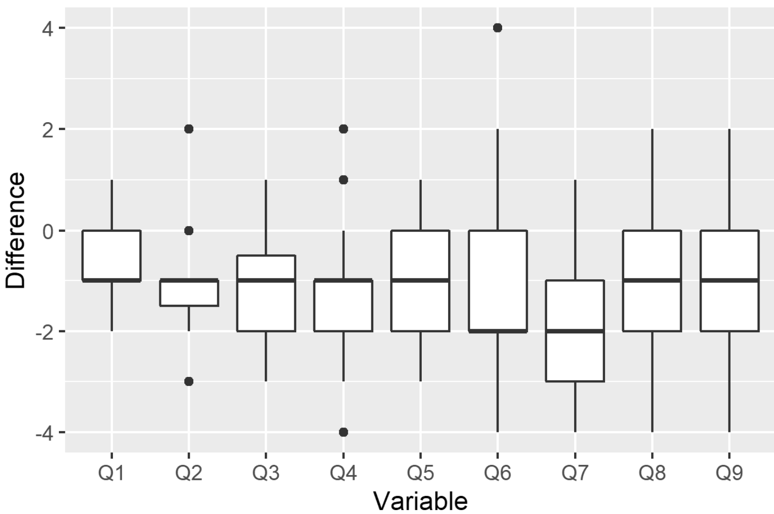


Figure A2. Boxplots of the differences in the scores (before – after) assigned to each question before and after the changes to the system.



Publication-III Questions

- Q1-The recommendations are **relevant** to my activities
- Q2-The recommendations are **surprising** to me
- Q3-The recommendations **differ significantly** from each other
- Q4-The recommendations are **useful** to me
- Q5-I am satisfied with the **language** of recommendations
- Q6-The recommendations provide me with **novel** information
- Note: The dependent variables are highlighted in **bold**
- Likert Scale:

Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree

Figure A3 shows boxplots of the scores assigned to each of the 6 questions before and after the changes were implemented in the system. The shifts in the boxplots towards larger values after the changes were implemented would indicate better acceptance from the students of the modified system. Figure A4 shows boxplots of the differences in the scores assigned to each of the 6 questions before and after the changes (before – after). This figure reveals that question 2 represents the characteristic of the system with the greatest impact on students' perception of improvement in the system.

Figure A3. Boxplots of scores assigned to each question before and after the changes to the system.

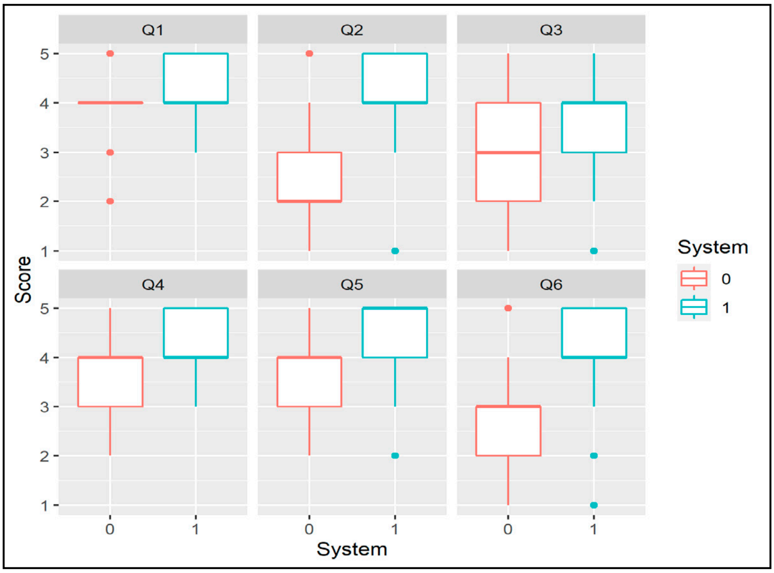
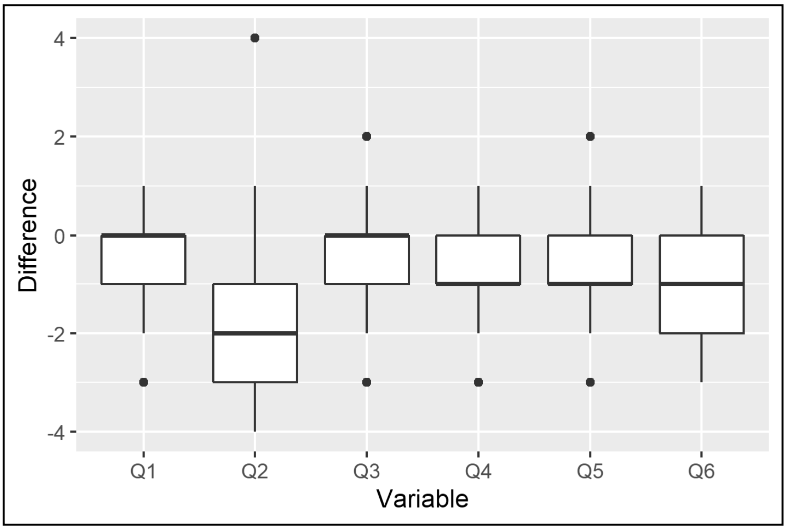


Figure A4. Boxplots of the differences in the scores (before – after) assigned to each question before and after the changes to the system.



Publication-IV Questions

- Q1-The recommendations are **useful** for me
- Q2-The recommendations are **relevant** to my activities
- Q3-The recommendations provide me with **novel** information
- Q4-The recommendations are **surprising** to me
- Q5-The recommendations **differ significantly** from each other
- Q6-The recommender **interface provides sufficient information**
- Q7-The recommender provides an adequate way for me to **express my preferences**
- Q8-The items recommend to me took my **context** requirements into consideration
- Q9-The system **helps me understand** why the items were recommended to me
- Q10-I found it easy to **alter the outcome** of the recommended items due to my preference change
- Q11-I understood **why items were recommended** to me

Note: The dependent variables are highlighted in **bold**

Likert Scale:

Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree

Figure A5 shows boxplots of the scores assigned to each of the 11 questions before and after the changes were implemented in the system. The shifts in the boxplots towards smaller values after the changes were implemented would indicate a negative impact on students' opinions of these changes. Figure A6 shows boxplots of the differences in the scores assigned to each of the 11 questions before and after the changes (before – after). In this case, question 5 seems to be the only characteristic of the system that had no impact on students' perception of the modified system.

Figure A5. Boxplots of scores assigned to each question before and after the changes to the system.

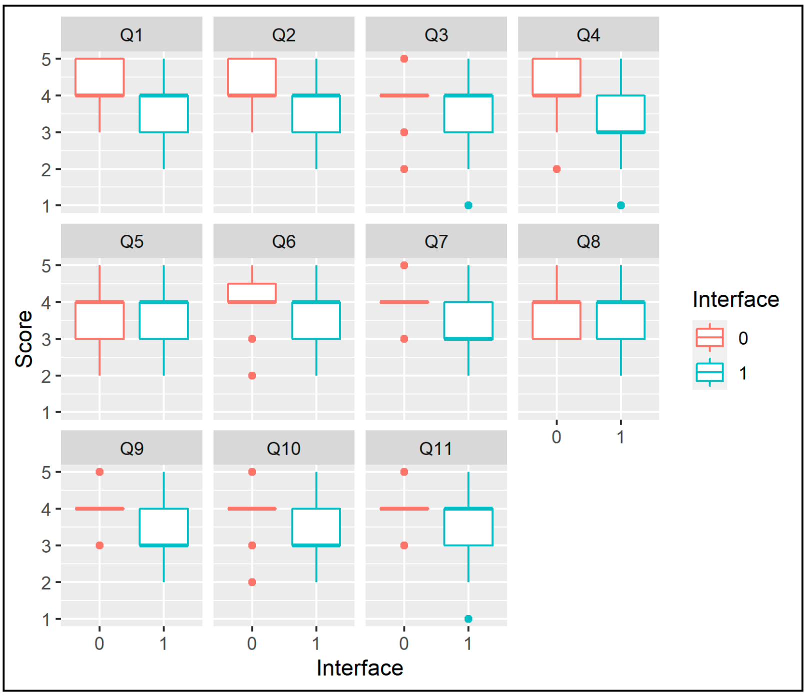
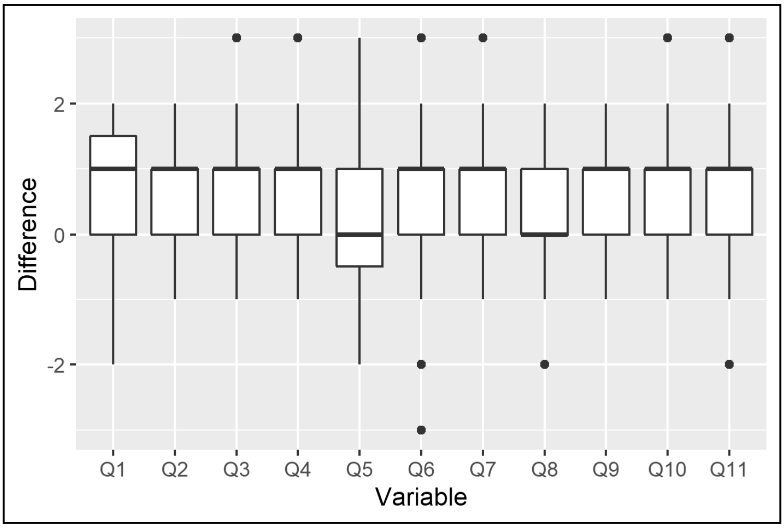


Figure A6. Boxplots of the differences in the scores (before – after) assigned to each question before and after the changes to the system.



In the second read, boxplots of the scores assigned to Questions 3, 4, 6, and 9 before and after the changes were implemented to the system indicate a positive impact on students' perception of the system. While for Questions 1, 2, 5, 7, 8, 10, and 11 the scores assigned seem to be very similar before and after the changes (Figures A7 and A8).

Figure A7. Boxplots of scores assigned to each question before and after the changes to the system.

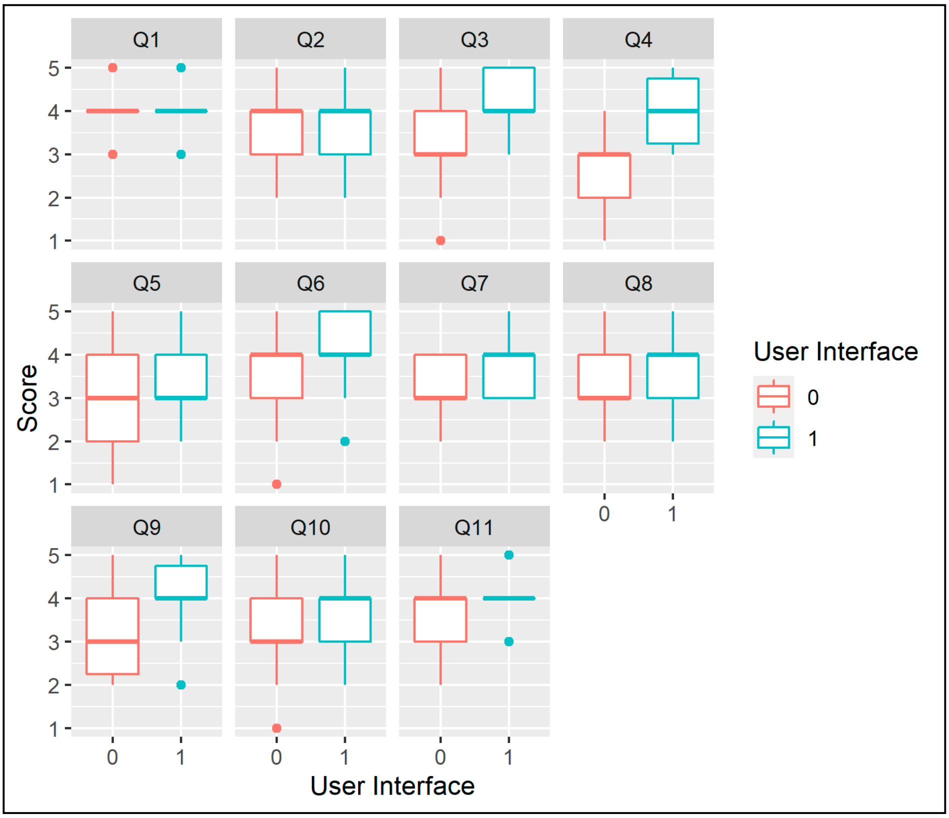
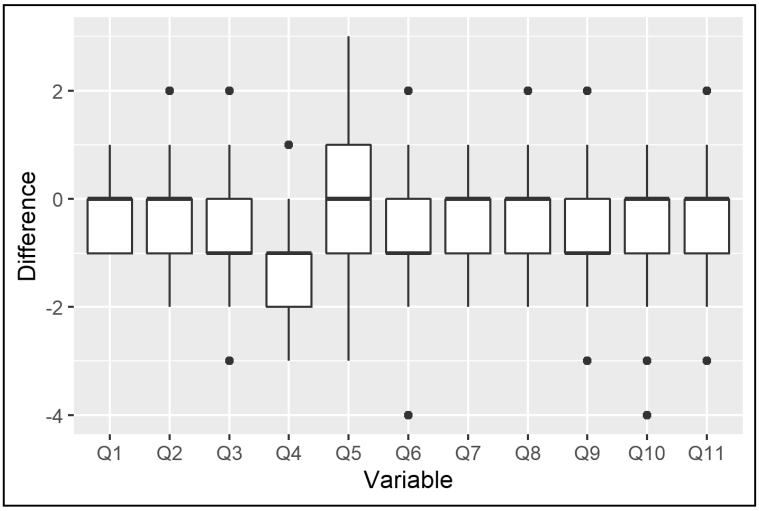


Figure A8. Boxplots of the differences in the scores (before – after) assigned to each question before and after the changes to the system.



Publication V and all others using NASA-TLX

NASA-TLX Questionnaire (For All Studies Conducted)

- Demand: How **mentally demanding** was the task?
- Demand: How **physically demanding** was the task?
- Demand: How **hurried** or rushed was the pace of the task?
- How **hard** did you have to work to accomplish your level of performance?
- How insecure, discouraged, irritated**, stressed**, and annoyed were you?

Note: The dependent variables are highlighted in **bold**

Likert Scale:

High						Medium								Low						

Task load of JabRef vs Google Scholar in Publication IV

Figure A9 shows Boxplots of the scores assigned to each of the 6 questions before and after the changes were implemented to the system for the first. Questions 1, 2, 3 and 4 show similar boxplots (distributions of scores) before and after the chances were implemented. While for Questions 5 and 6, the boxplots are shifted towards greater values after the changes were implemented indicating a negative impact on student's perception of task load. Figure A10 shows Boxplots of the differences in the scores assigned to each of the 6 questions before and after the changes (before – after). These boxplots confirm the impression given by Figure A9.

Figure A9. Boxplots of scores assigned to each question before and after the changes to the system in the first read.

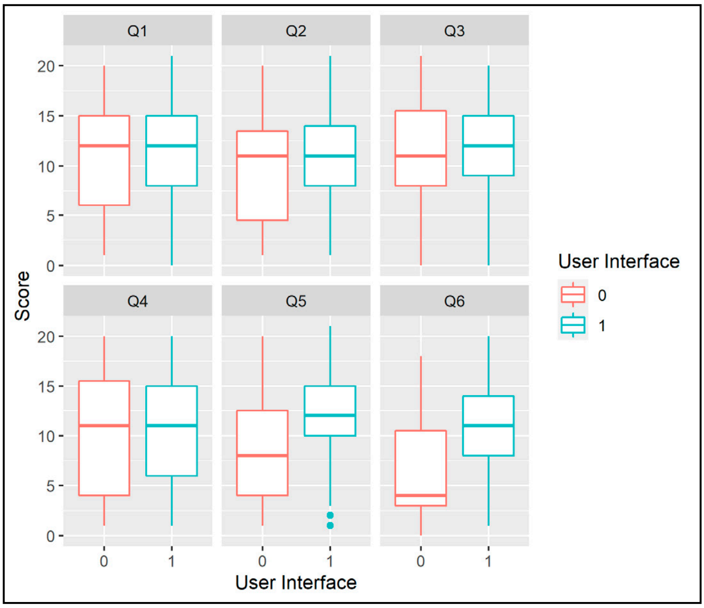


Figure A10. Boxplots of the differences in the scores (before – after) assigned to each question before and after the changes to the system for the first read.

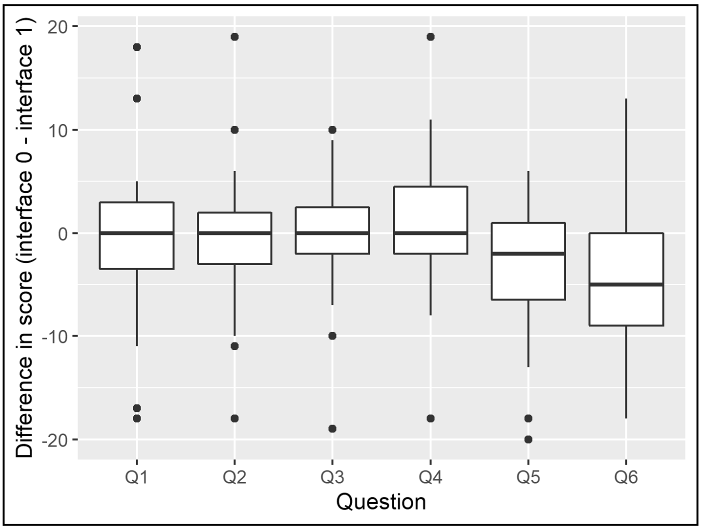


Figure A11 shows Boxplots of the scores assigned to each of the 6 questions before and after the changes were implemented to the system in the second read. For all the questions the boxplots corresponding to user interface 1 are shifted towards smaller values indicating a negative impact on student's perception of task load after the changes were implemented. Figure A12 shows Boxplots of the differences in the scores assigned to each of the 6 questions before and after the changes (before – after). These boxplots confirm the impression given by Figure A12.

Figure A11. Boxplots of scores assigned to each question before and after the changes to the system in the second read.

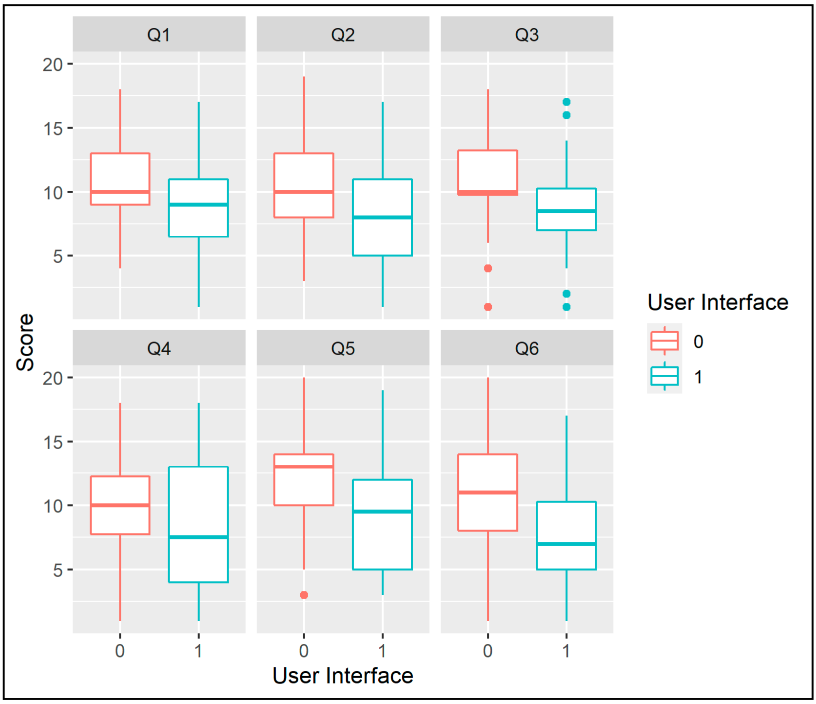


Figure A12. Boxplots of the differences in the scores (before – after) assigned to each question before and after the changes to the system for the first read.

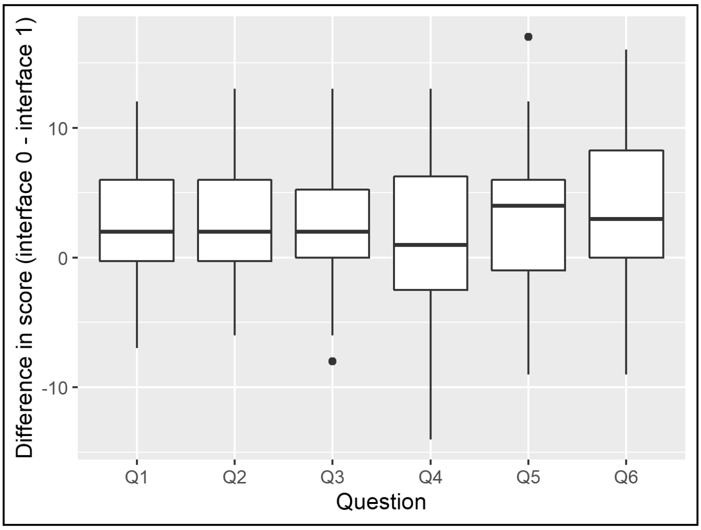


Table -A1- Interquartile Range Of Publication-II Dataset

Question. No	**Baseline System**	**Advance System**
1	1	1
2	1	1
3	2	1
4	2	1
5	1	1
6	2	1
7	2	1
8	2	1
9	2	1

Table -A2 -Interquartile Range Of Publication-III Dataset

Question. No	Baseline System	Advance System
1	0	1
2	1	1
3	2	1
4	1	1
5	1	1
6	1	2

Table-A3-Interquartile Range of Publication-IV dataset

Question. No	Baseline System	Advance System
1	1	1
2	1	1
3	0	1
4	1	1
5	1	1
6	0	1
7	0	1
8	1	1
9	0	1
10	0	1
11	0	1

Part B

The Publications

PUBLICATION I

Serendipitous Recommenders for Teachers in Higher Education

Ahmad Hassan Afridi

Handbook of Research on Faculty Development for Digital Teaching and Learning (pp. 333-353). IGI Global. DOI: 10.4018/978-1-5225-8476-6.ch017

Chapter 17
Serendipitous Recommenders for Teachers in Higher Education

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ABSTRACT

Currently, most of the recommender systems that are in a prototype or deployed stage are primarily accuracy oriented. This chapter focuses on teacher preferences for designing serendipity-oriented recommender systems for academic activities. Reports on relevant literature about serendipitous recommenders and fac ulty empowerment with such tools, a focus group study of teachers for some industrial recommender system platforms, and a use case on instructor use of recommenders to inform and support recommendations for lectures are covered. Further, a survey of students to explore the feasibility of student-teacher serendipitous activities and operations are also reported. The results from all three studies show that serendipity has a major role to play in the future. The author surveyed the literature on standard digital libraries and used questionnaire-based data collection and standard statistical methods to evaluate the responses.

INTRODUCTION

Serendipity is characterized by surprise, an "aha moment" as described by Makri, Blandford, Woods, Sharples, & Maxwell (2014). If we are fortunate, we may encounter it often in our daily lives. Our day-to-day working and personal lives benefit from these "happy accidents" (López-Muñoz, Baumeister, Hawkins, & Álamo (2012) and experiencing serendipity has the potential to make our lives better. Existing secondary literature has described the usefulness of serendipity (McCay-Peet & Toms, 2015). Today, a broad range of information communication technologies present evidence of serendipity being facilitated digitally. As we discuss serendipity, we must understand that serendipity has many forms, meanings and still remains subjective from one user to another (Knijnenburg & Willemsen, 2015) .

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Serendipity in learning is new and only a few conceptual studies are available as studied by (Giordano, 2010; He, Parra, & Verbert 2016) . These studies are mostly focused on digital libraries (Sugiyama & Kan, 2011). They have demonstrated the usefulness of serendipity in learning, however, most of these studies remain as software prototypes of laboratory experiments. Real-world examples of how serendipity can be useful are not available for teachers and it is thought that learning has never benefited from serendipity, resulting in little research (Liang, 2012). As we further explain the problems associated with serendipity, we must understand why learning has never benefited from its occurrence. First, serendipitous outcomes are not usually understood immediately and sometimes it may take time to fully understand the potential of the outcome (Yaqub, 2018). Second, the general mindset toward serendipity is that it is a matter of chance and it can neither be designed nor engineered (Thudt, Hinrichs, & Carpendale 2012).

Faculty members are helping students explore new horizons. In university environments, faculty help students find new research topics in a new and related area of work. In order to help students to further grow and to promote out-of-the-box thinking, finding new routes to approach existing problems requires "happy accidents." This approach may be even more useful if there is a system that facilitates it. As it currently stands, encouraging and sustaining serendipitous moments in education depends on each individual teacher's intellect and skills.

We are living in a world where teachers are increasingly utilizing technology (Shani & Gunawardana, 2011). Technology is being used by teachers via simulators, analytics systems, virtual reality systems, and animation, to name a few. From the classrooms to the labs, there is hardly a single field that has not harnessed the benefits of learning technology. In order to fully realize and take advantage of 21st-century learning, many technologies have attempted to make use of educational pedagogies to help faculty members steer the course of the classroom (Jivet et al., 2017). Many authors have worked it into learning technologies and there are ever-evolving mechanisms to develop novel teaching tools. Whether it is online open courseware (MOOC) or a physical classroom, technology-based learning is taking over traditional methods of teaching (Verbert et al., 2012) . There are some systems, such as YouTube, Amazon, and reference management software that use recommender systems and have the potential to unleash serendipity for users. Traditionally, serendipity has been explored in technology via music, friends and so forth (Steck & Johnson, 2015).

Recommender systems are one of the learning technologies that can harness serendipity. Recommender systems are software programs that suggest interesting items to users (Manouselis, Drachsler, Verbert, & Duval, 2013). These recommender systems are embedded into conventionally available websites such as YouTube, Amazon and some reference management software systems, such as Mendeley, JabRef, etc., that provide useful recommendations to its users. These platforms are also used by teachers in different ways. In order to benefit from serendipity in an educational setting, we have to look for existing technology that can be used to experience it or develop a new way of using it. There is a strong potential for recommender systems to facilitate serendipitous information to teachers—which can be beneficial in a number of ways as it can automate the process of suggesting useful and novel information. While many recommender systems have attempted to offer serendipity in teaching (Giordano, 2010) there are no case studies that present teachers with such options or the user interface of such an information system.

Teachers' experiences with serendipity are still unknown, and their understanding and use of it in teaching is an unstudied phenomenon. We are testing the water by conducting this study and by working on RecSys enabled with serendipity for learners (Drachsler, Hummel, & Koper, 2008). We are interested to know how teachers think about serendipity, if they have experienced it using commercial platforms, and what were their experiences and preferences. The teacher's perspective on serendipity and its usefulness in education are necessary for future studies.

This book chapter is intended to help university faculty understand the importance of serendipity in pedagogy. This chapter examines user experience studies of the aforementioned technologies. The faculty members were distributed questionnaires for data collection. This work can be inspiring for the scholar if they are planning to conduct large-scale studies on serendipity usefulness and its impact on teaching. Further teacher experiences with technology that offer serendipitous information should continue to be studied, and this chapter can act as a starting point. Understanding faculty preferences for serendipity-oriented user interface design will lead to beyond-accuracy application opportunities and foster a new, diverse set of applications. This study will help us better understand user interface problems and issues for expressing and facilitating serendipitous recommendations by recommenders.

BACKGROUND

In order to understand faculty members' experiences and outcomes after using a serendipitous recommender system, several authors' approaches are discussed. The literature helps us to understand the dynamics of the user interface of recommender systems, serendipity, and further understand its relationship with teaching.

A Word on Serendipity

Yaqub's (2018) work on serendipity discusses the origin, flow, and results of the phenomenon of serendipity. According to the author, serendipity has its origin in the uncertainties involved in the process of science. Various instances in the history of science tell us that useful outputs and outcomes of the scientific process have often been observed from an uncharted route. These outputs and outcomes have played a major role in further strengthening the scientific community's belief in serendipity. The author then presents the typologies of serendipity and explains how various forms of serendipity and its implications have changed the course of the scientific journey. The author specifically emphasizes the role of experimentation and discusses the reluctance of the scientific community regarding serendipity. Yaqub ultimately concludes that the occurrence of serendipity can have a huge impact on technology-based teaching and provides evidence that encourages the research community to develop more case studies on the topic.

Recommender Systems and Learning

Recommender systems are at the forefront of exploring diversity, novelty, serendipity and usability of recommendations (Fazeli et al., 2016), also called beyond-accuracy experience. They are being studied in academia but there are very few specific case studies, prototypes, and applications for faculty members. Initially, recommender system research focused on accuracy-oriented recommendations (He, Parra, & Verbert, 2016); however, additional aspects such as novelty, diversity, interactivity, and transparency later attracted researchers' attention. As more studies emerged about beyond-accuracy recommenders (Iaquinta et al., 2008), many applications emerged–particularly in learning science–that go beyond accuracy. Castellano and Martínez (2009) have studied the use of recommender systems for students helping students in their academic journey at the high school level.

Researchers have approached serendipity via algorithms in recommender systems (Akiyama, Obara, & Tanizaki, 2010; Eagle, 2004; Maccatrozzo, van Everdingen, Aroyo, & Schreiber, 2017; McCay-Peet, Toms, & Quan-Haase, 2016; Yamaba et al., 2013; Yaqub, 2018). Kotkov, Veijalainen, and Wang (2016) have studied the process of serendipity in recommender systems, focusing on developing definitions of serendipity, state-of-the-art approaches, and determining ways to progress forward with researching a concept that has a lot of "subjectivity" associated with it due to the emotional dimension that is often present with it. Researchers have further discussed architecture and the implementation of models of serendipity in a recommender system. de Gemmis, Lops, Semeraro, & Musto (2015) investigated serendipity in a recommender system by implementing a graph-based recommender system. The authors of the study discussed some commercial recommender systems like Amazon that implement serendipity into their recommenders using statistically improbable phrases. The researchers' emphasis was on the explicit feedback in a recommender system.

Other researchers have focused on a broader area of the digital information system (Makri et al., 2014), arguing that serendipity cannot be created but merely influenced. Given this assumption, it is important to study the serendipity-seeking approaches in applications. The "aha moment" used for relating user experiences has been used to explain the phenomenon. Liang (2012) presented three studies by designing a social clock, a local radio, and a social capsule. The idea, in this study, is that serendipity should be studied as a new quality of user experience and observing the user interaction with such an information system is beneficial. The study provides evidence showing that interaction design for computers has changed and suggests that the emergence of new psychological needs has made conventional interaction obsolete. Maccatrozzo et al. (2017) have introduced a new artifact to measure a user's ability to appreciate serendipity and serendipitous information. Their study shows that an information system designer's perspective and aims are changing toward designing beyond-accuracy experience and human information needs that are not conventionally present.

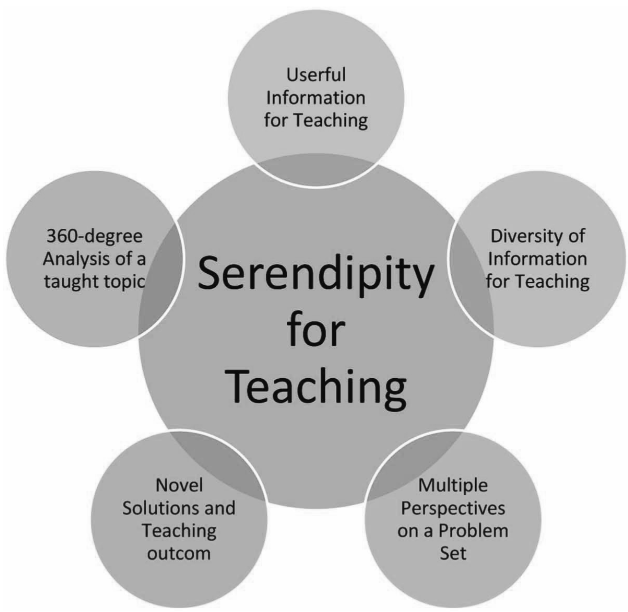
Afridi (2018a) has explained the use of the interactive recommender system for generating serendipity in educational environments. This study focused on the user's (learner's) discretion of using interactivity to move toward accuracy or beyond-accuracy in order to explore academic resources. The study can inform faculty members about using a recommender to redirect their pedagogical approach to teaching a course. Another study by Afridi (2018b) discusses the potential for providing faculty members with serendipitous recommender systems. Recommender systems have also been studied for their potential to visualize serendipitous recommendations for learners (Afridi, 2018c). The definition of academic resources, in this context, includes books, educational documentaries, and movies. Code snippets, engineering equipment, and manuals are also included. Since the recommender systems are now being integrated into major commercial websites, such as Amazon, Google, and YouTube, it is imperative to study serendipity and its impact on the user experience. Serendipitous recommender systems have their strengths and weaknesses. First, serendipitous recommendations may increase the probability of purchasing books and, yet, the reader may not be fully able to take full advantage of serendipity. The time required to cover a diverse set of books and other materials might create confusion and conflicting views on understanding. Ultimately, the faculty must decide when and how serendipity can benefit instruction. Faculty members are the driving force in the classrooms and providing opportunities for serendipity might be achieved by optimizing a relevant set of diverse sources of learning materials or by ranking study materials according to students' needs. Bringing efficiency to learning is of utmost importance to the faculty member's mission as an educator.

The educational impact of the serendipity can be measured by how well it is able to facilitate achieving objectives according to Bloom's Taxonomy. Moving up the Blooms Taxonomy ladder, it is imperative to understand, develop, and test how well serendipity can foster effective pedagogy. From teaching to bridging the gap between students, between theory and practice, and between concept and understanding, serendipity can provide useful, yet surprising, recommendations. All of these educational impacts can be achieved but they come at a cost. Decision support (Almutawah, 2014) as related to serendipity in teaching and learning has attracted some attention in research (Giordano, 2010).

Figure 1 shows how serendipity can diversify and bring novel course material while also adding multiple perspectives and useful information to courses.

A faculty member's main mission in the classroom is to foster and grow student intellect with as many diverse viewpoints as possible. Another primary mission is to encourage students to develop problem-solving abilities in order to achieve course objectives in a timely manner. As faculty members are completing course-related tasks, there is a need for developing diverse methods of teaching, approaches to topics, and multiple perspectives about specific topics (Kunaver & Požrl, 2017). Courses that are crafted using specifics example and particular books often lead to a specific route for learning. There are benefits as the course includes specific resources and a concrete timeline, but it is very important that this is the best route. In other words, should we look at a topic from a specific perspective or do we need a 360-degree evolution of a concept? Faculty members should adopt an approach that involves

Figure 1. Serendipity and its impact on teaching



recommending academic resources that are diverse in nature. The diversity could be manifested in an unexpected recommendation that is new and useful to both the learning objectives and the learner. As already described, serendipity provides useful surprises to the user (learner). Serendipitous recommenders can provide the same intellectual feats through a new route of understanding. This phenomenon will encourage the learner to listen, read, and learn about multiple points of view. Along with introducing diverse content, this approach to teaching will result in novel pedagogical methods. Faculty members will explain their subject matter via multiple routes and with perspectives. It is believed that effectiveness of instruction depends on teachers' skills and their command of the subject; however, recommender systems with a serendipity feature can further support faculty members' efforts in progressing up the Bloom's Taxonomy ladder.

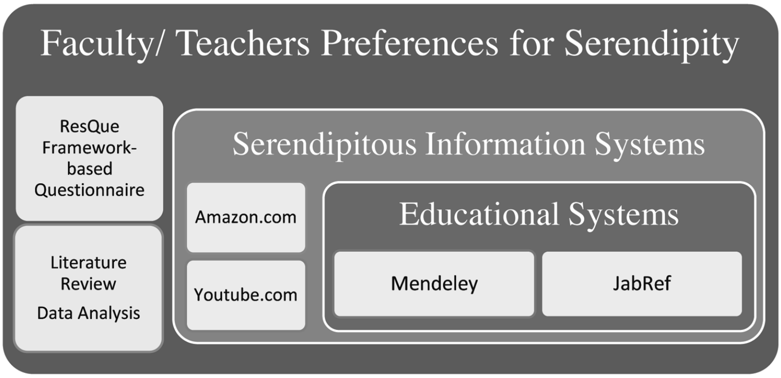
According to Yaqub (2018), there are various kinds of serendipity. One kind entails finding a solution to a problem in the future. A second kind relates to finding a solution through an unexpected route. A third might be finding a novel solution for a known problem and, finally, a fourth is finding a solution to an unknown problem. These four kinds of serendipity in a recommender system can offer four different approaches for faculty members in the classroom, and a recommender supporting such missions can potentially collect results on totally serendipitous learning outcomes. This case can be particularly interesting for teaching technical subjects such as software engineering and coding. Students can learn about coding on the same problem using multiple programming languages. Recently, these recommender system usage trends have been seen in software engineering and coding.

We can imagine that a future of serendipity-oriented recommenders will aid faculty members on a 'serendipitous mission.' As there are not many studies on the application of serendipitous recommender systems in academia, it is imperative to explore the science of serendipity and recommenders for beyond-accuracy implementation for academics, and for exploring new research on a faculty member's usage of a recommender system as an intellect multiplier.

This chapter forwards the case for additional research by pointing to a study involving faculty members at the Institute of Management Sciences, Peshawar by examining serendipity preferences for user interfaces, particularly in regards to recommender systems in digital online resources (recommenders), such as Youtube.com and Amazon.com, and educational recommenders, such as Mendeley and JabRef (references management software).

Figure 2 charts the study framework for this chapter. Technology Enhanced Learning (TEL) recommenders and Digital Online resources are conventional non-academic recommenders available to faculty members. Faculty serendipity preferences have been studied by collecting data in questionnaires in ResQue forms and they have also been studied for conventional recommenders used in education, such as YouTube and Amazon. Other state-of-the-art recommenders, such as Emerald, Google Scholar, and Mendeley, have been studied. We discuss the experience of both types of recommenders in the following sections. Both of the studies were conducted at the Institute of Management Sciences, Peshawar. The reason the study was conducted on faculty members was that the same studies were conducted on students with the output of multiple prototype recommender system software and interfaces. Around 100 faculty members participated and represent around 20-25 percent of the faculty. Low participation rates were due to the fact that faculty members were not initially aware of the use of the recommender system interaction and usage during learning. Secondly, most of the faculty preferred accuracy-oriented systems (i.e. they wanted suggestions/recommendations that were closely related to their course work), therefore, this left less room for the use of serendipitous recommendation systems. As a result, it was very difficult to elicit preferences for a user interface for a serendipity recommender system. However,

Figure 2. Study framework



this study did reveal a glimpse into the preferences that will be useful for expanding perspectives into the user interface design and creating a more detailed study in the future. Furthermore, the study will be useful for extending the work of user-controlled serendipitous recommender system user interface design (Afridi, 2018b)

Recommender Experience for Teaching: A Study of YouTube and Amazon Recommenders

There are very few studies that discuss the state-of-the-art serendipity recommendations for faculty members. This part of the chapter reports on a study conducted to understand faculty members' preferences toward serendipitous recommender systems and its applications in lecture preparation and delivery. The secondary aim of the study was to present a perspective of state-of-the-art platform usage in education at the higher education level. The research also helps document requirements for future studies of beyond-accuracy recommenders for faculty members. The study is designed to evaluate user experience (a subjective evaluation) of two recommenders, YouTube and Amazon, based on studying evaluations (Erdt, Fernandez, & Rensing, 2015; Fazeli et al., 2016). The questions were formulated as proposed in the ResQue model (Pu & Chen, 2010). The questionnaire (Appendix-1) was distributed to faculty members who were asked about both the recommender system and their experiences with various aspects of the commenters. The data collected was then processed for multivariable analysis and linear discriminate analysis to examine the difference between both recommenders and observation of the serendipity in both recommenders. The calculations for observations are as follows. Multivariate analysis and linear discriminant analysis required input from a dataset garnered for both recommenders. The dependent variable and independent variables were fed into the statistical package for processing. In this study, the author used SPSS 20. Dependent variables were serendipity, transparency, contextual interface adequacy, and user control of the recommender set. Independent variables included both recommenders driving YouTube and Amazon, respectively. Furthermore, the author also performed clustering on a dataset for exploring patterns of faculty members' preferences.

The results from analyzing user control, novelty, diversity, context compatibility, and trust are given as follows. The author applied discriminant analysis on data from 20 faculty members who participated in the survey for evaluating YouTube and Amazon.com recommenders. Zero (0) represents YouTube and one (1) represents Amazon.com.

Table 1, Table 2 and Table 3 and 4 show that there is no significant difference between these two recommenders. Therefore, the faculty members had similar user experiences with respect to serendipity from both platforms. In Table 2, diversity has been used to measure serendipity. In the equality group of

Table 1. Tests of equality of group means

	Wilks' Lambda	F	df1	df2	Sig.
User Control	.995	.174	1	38	.679
Trust	.981	.716	1	38	.403
Context	.949	2.027	1	38	.163
Novelty	.915	3.526	1	38	.068
Diversity	.999	.027	1	38	.870

Table 2. Covariance matrices

Recommender System		User Control	Trust	Context	Novelty	Diversity
0	User Control	.576	-.003	.326	-.316	-.082
	Trust	-.003	.997	.379	-.053	.392
	Context	.326	.379	.695	-.158	.011
	Novelty	-.316	-.053	-.158	1.053	-.158
	Diversity	-.082	.392	.011	-.158	.997
1	User Control	.576	.437	.179	.389	.321
	Trust	.437	.747	.558	.505	.442
	Context	.179	.558	.884	.411	.274
	Novelty	.389	.505	.411	.989	.747
	Diversity	.321	.442	.274	.747	.832
Total	User Control	.564	.218	.256	.051	.115
	Trust	.218	.866	.482	.259	.403
	Context	.256	.482	.810	.185	.133
	Novelty	.051	.259	.185	1.087	.279
	Diversity	.115	.403	.133	.279	.892

a. The total covariance matrix has 39 degrees of freedom.

Table 3. Wilks' lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.868	5.037	5	.411

Table 4.

Reliability Statistics	
Cronbach's Alpha	**N of Items**
.780	21

means, novelty is showing some effect. More elaborate results could be obtained with a larger sample size beyond the 20 faculty members who participated. For faculty members, there can be a temporary specific website /platform to gather serendipitous recommendations. Both platforms needed serendipitous functions or beyond-accuracy options.

Faculty members' awareness and experience with serendipity are of the utmost importance. The faculty members' exploration of novelty and beyond-accurate study material on YouTube and Amazon is central to the basic understanding of the serendipity-oriented recommender system developed for learning. In this section, the author specifically discusses the use case scenarios related to serendipitous recommendations used by a faculty member for course material exploration.

Faculty members generally use YouTube and Amazon for computer science lecture presentation and course exploration. A faculty member at the Institute of Management Sciences, Peshawar, prepared artificial intelligence lectures for the computer science program at the undergraduate level for two weeks. Both recommended systems, YouTube and Amazon, were rigorously used to acclimate faculty with the user interface of the websites. The methodology for the faculty members performing serendipitous searches and obtaining recommendations and lecture preparation using both recommended systems has been described in the following section.

The faculty member first prepared keywords, such as 'artificial intelligence' for use in our searches. The terms 'artificial intelligence lecture' and 'artificial intelligence books' were also used. Then, the faculty member inserted keywords into both search engines. The result was a list of search results and recommendations in the suggestion box. The search results were reviewed for their accuracy and relevance to our goals. Then, the author observed that recommendations were also presented as suggestions in the user interface. Based on the expertise of the searching faculty member, the serendipitous results in the recommendations were then examined. The author did find many useful and interesting items from the recommenders. The sequence of participation activities is described below.

1. Searching YouTube and Amazon.
2. Viewing generated result (recommendations).
3. Locating new, useful search results in recommender (serendipity).
4. Repeating for other lectures.

The results for the participation activities are displayed below in Table 5.

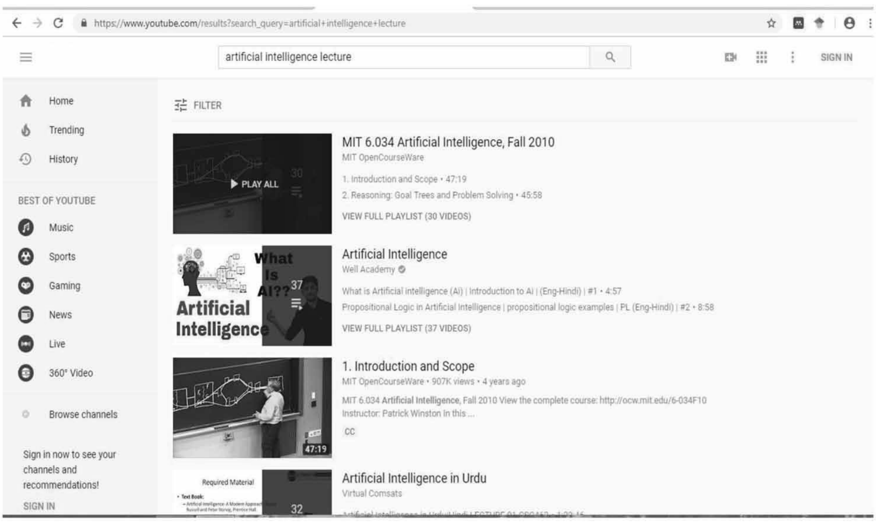
The screenshot for both searches and recommendation activities are displayed below.

Figures 3 and 4, and Figures 5 and 6 show the results returned by search engines and recommendations suggested by YouTube and Amazon.com, respectively. One of the observations made during the preparation of lectures was that serendipity differs from one day to another. If any recommendation is serendipitous, it may occur the next day or even in the next search. This makes the recommendation a matter of subjectivity. There is also a diminishing impact of serendipity after some time of seeing all

Table 5. Results from search activity

Number of AI faculty participating	1
Number of Lectures	4 lectures
Number of Searches	2 searches
Number of Recommendations	72 recommendations per page for Amazon Continuous playlist per page in YouTube
Number of Serendipitous Results	3 results per page in Amazon 10 results per continuous playlist in YouTube

Figure 3. YouTube video search results



recommendations related to the topic. So, timing and context are of the utmost importance in designing and evaluation of such serendipity oriented systems. Along with algorithmic additions, it is important to find a relevant interface to observe serendipity and controls in the interface. Therefore, user controls and widgets are necessary for faculty use in order to exercise serendipity.

Recommender Experience for Teaching, A Study of Academic Recommenders

The aim of this study was to evaluate various recommender systems used in academia for literature suggestions. This study was conducted at the Institute of Management Sciences Peshawar. Out of 100 faculty members, only 25 faculty members used the recommendation feature. The others were either not using or did not seem to find the recommendation feature to be useful. We distributed a questionnaire based on the ResQue model for recommender system subjective evaluation as described by (Fazeli et al., 2016). The respondents were faculty members at the Institute of Management Sciences, belonging to

Figure 4. Serendipitous recommendations from youtube.com

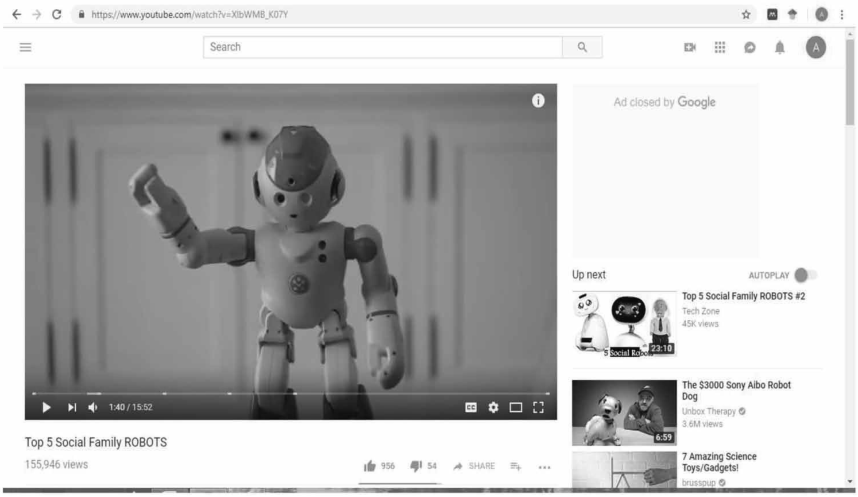
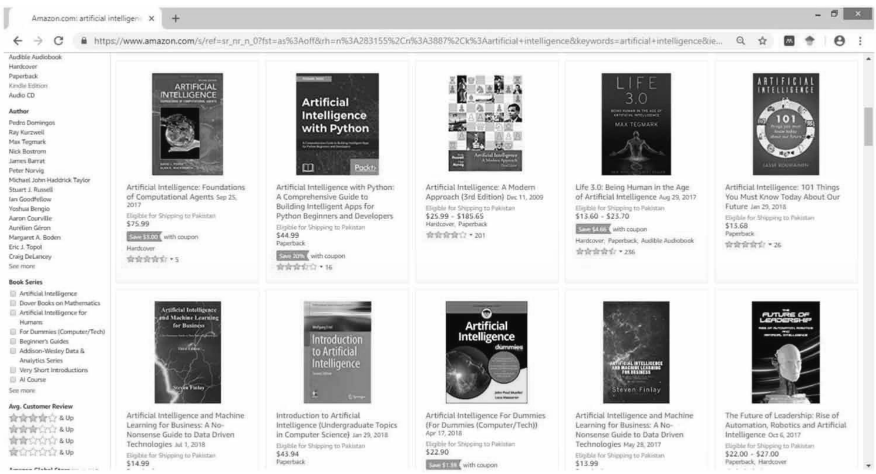
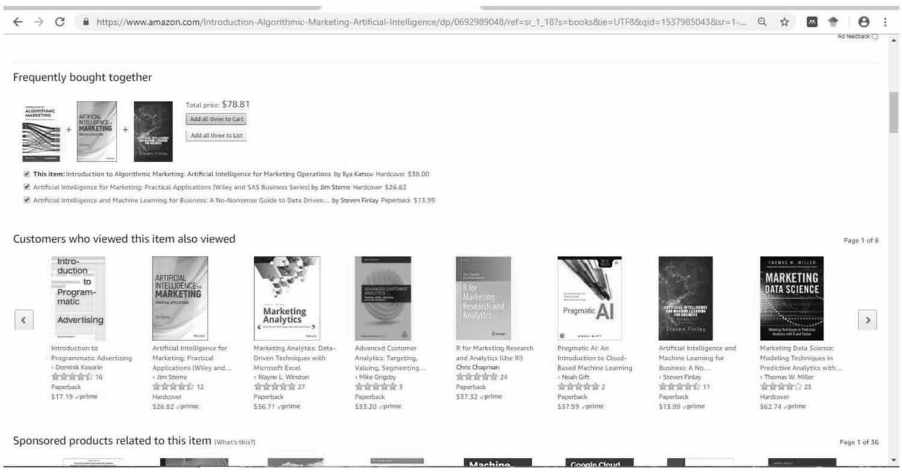


Figure 5. Amazon.com search results



management, social sciences, and computer science disciplines. The data was collected for the following recommender systems: JabRef, Mendeley, Google Scholar, Emerald Insights, and Research Gate. The faculty members were asked about their experiences with one of the mentioned recommender systems. Since the participants were either not very familiar with the recommendations systems or did not rely upon the services, we were unable to create a conclusive design recommendation. The following charts

Figure 6. Serendipitous recommendations from amazon.com



show a few dimensions that may inform future experiments and prototyping of serendipitous-oriented recommendation system development. The results of the collected data show some promising trends that promote a better understanding of recommender system usage in academia and its usefulness in recommender's user interface design.

Study Results

Figure 7 shows trends in study material recommended by faculty members and teaching experience. We learned that there is no substantial correlation among these factors. However, it was noted that serendipity and recommendations needs from a recommender system have not yet been fully examined in academia. As most of the lecture-based academic institutions follow specific sources outlines, it is worth investigating the reasons why faculty members do not need serendipitous recommendations for their courses.

Figure 8 shows that with the Emerald Insight recommender and Mendeley recommender, users experienced control while using the recommender systems. Figure 9 shows that users of JabRef suggested the highest number of reading material to students, whereas Mendeley recommendation users had a high number of recommendations for reading material. Figure 10 shows that Google Scholar and Mendeley have diversity in their recommendations. The diversity is an important component of serendipity recommendations. Figure 11 shows that Google Scholar, Mendeley, and ResearchGate take the context of the user into account when recommending academic material. There were not many users for Emerald Insights and JabRef, so it cannot be conclusively determined whether or not there was a user perceived context awareness in the recommender.

Figure 7. Study material and teaching experience

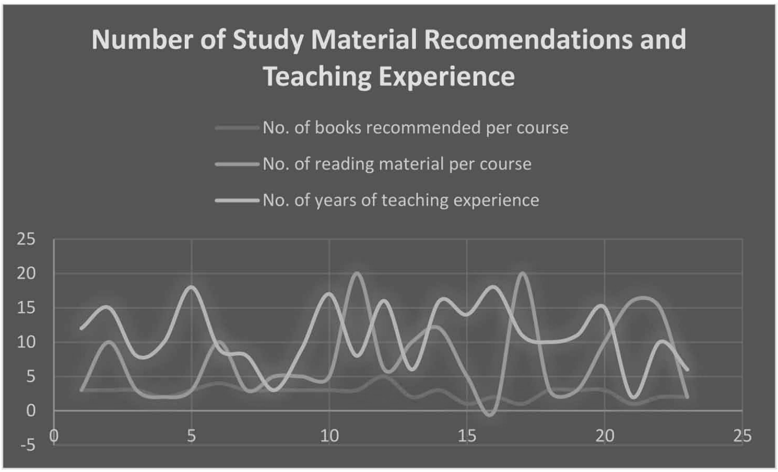


Figure 8. User control and recommender systems

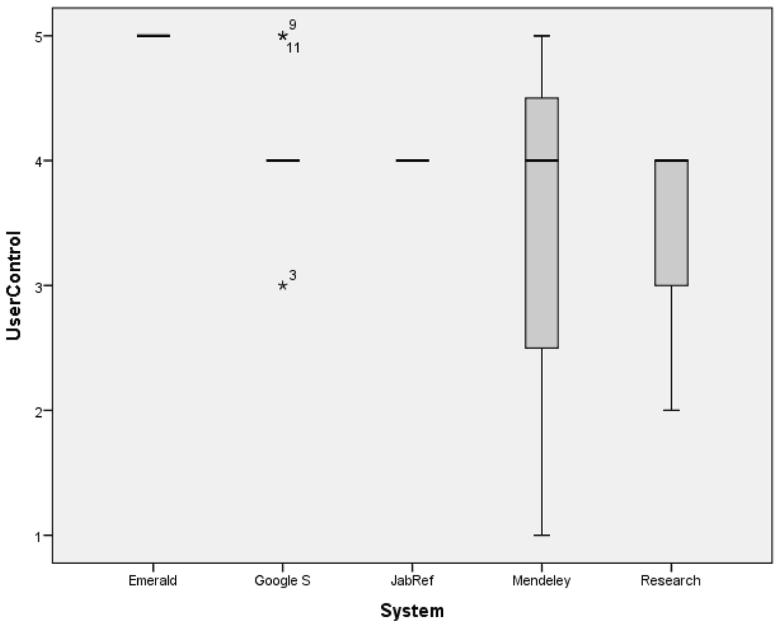


Figure 9. Reading material per course and recommenders systems

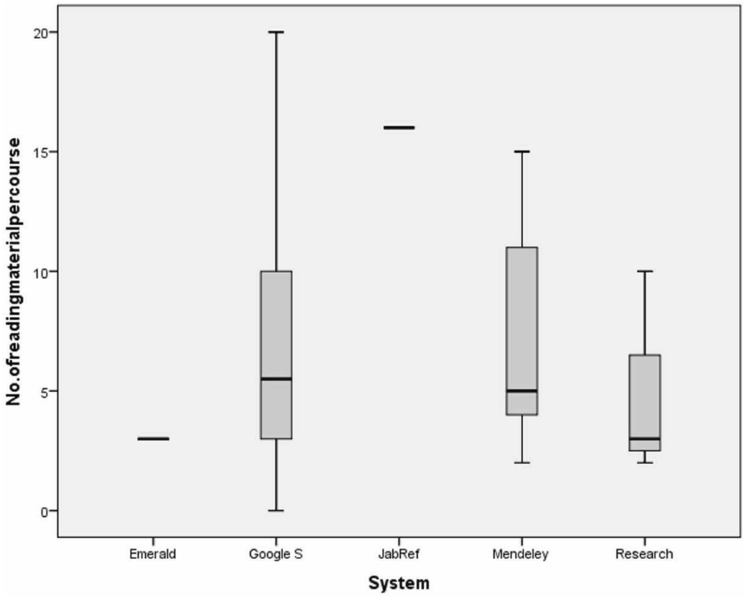


Figure 10. Diversity of recommendations and respective recommender systems

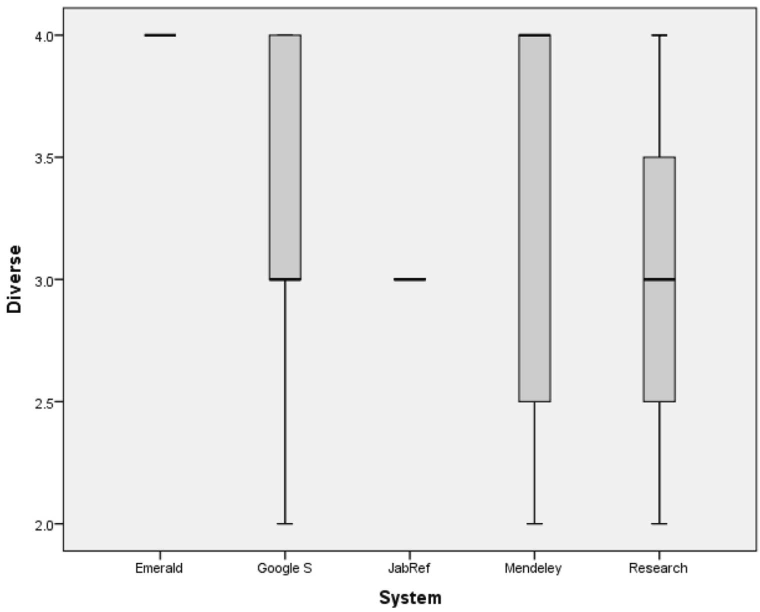


Figure 11. Context awareness and recommender system

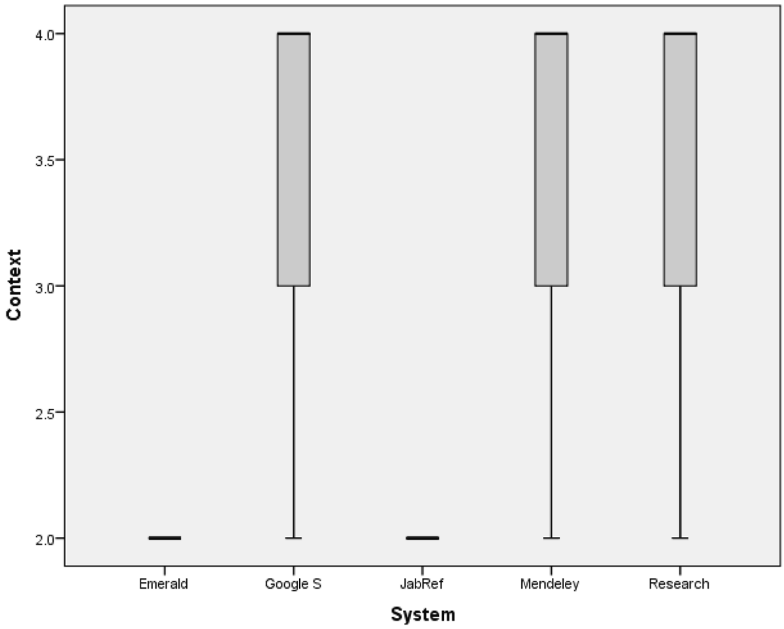


Table 6.

Reliability Statistics	
Cronbach's Alpha	**N of Items**
.780	21

SOLUTIONS AND RECOMMENDATIONS

We present a solution to the problem discussed in the study that follows. The work done by Afridi (2018b; 2018c) can be applied and extended to faculty members. Prototype and case studies of the user interface should be recorded. New user controls, such as serendipity sliders and visualization techniques driving user studies, should be incorporated and presented to faculty members.

We present some recommendations for designing user interfaces that help facilitate faculty in using serendipitous recommender systems. They are as follows. Serendipitous recommendations are quite new to the academic environment, particularly in terms of explicitly using the user interface feature. Commercial websites such as YouTube and Amazon.com that are used in learning environments should enable widgets and other user controls that are specially designed to gain the attention of faculty. For example, Khan Academy lectures are mostly hosted on YouTube and, therefore, such services can benefit from serendipitous recommendations and discovery-oriented user controls.

Second, reference management software should integrate recommender systems in such a way that the user interface for recommenders and serendipity controls are easily discoverable to users. It is important to mention that since there are very few users (faculty members) of recommender systems, discoverability of the interface is an important issue to address.

Third, making these recommender interfaces, including serendipity-focused user controls, available in the form of mobile apps and widgets can help familiarize the user with the benefits of the serendipity feature. One concern that surfaced during our interaction with faculty was that they did not perceive many benefits of serendipity-oriented recommendations. The serendipitous output is often affected by such problems, but two-way communication between recommenders and faculty can help us by recording when and how serendipitous recommendations helped the course.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Implications

The literature is full of prototypes and studies that test serendipity in a recommender system in the context of a lab and other controlled settings. One major constraint for the formal adoption of serendipity-oriented information or recommender systems is the very low number of people who are using and testing the prototype systems. As a result, we conclude that although serendipity has been an impactful tool for positively influencing outcomes and bringing a new experience to students, in the real world, human choices result in different outcomes. Instructors and students have diverse objectives and they may be different from time to time. Conventional platforms are only accuracy-oriented so far, and there is still a need for an interface that supports beyond-accuracy features of these platforms. Teaching using technology can only facilitate and, as the literature says, can only "influence" serendipity, rather than create it or objectively measure it. Therefore, it is imperative that new evaluation mechanisms are developed to help assess such recommender systems.

Key Lessons

The future of serendipitous recommender systems for faculty is principally based on the conventional platforms, providing serendipity and making faculty aware of the qualities of recommender systems. Long-term usage of such systems will open the door for instructors who embrace these features to improve the quality of their teaching and bring change to the education system. Making serendipity-oriented recommender systems available for faculty members and students can potentially bring both parties closer to a technology-enabled bridge where there is 'co-serendipity'–influenced or created. Faculty members and students are open to learning novel, relevant resources, and can create surprising outcomes and lasting impacts.

Limitations

As there are very few academic platforms that offer recommendation services, there are very few design considerations for serendipitous recommender systems. Focusing on the theory, user interfaces are changing as small samples generate studies that need to be evaluated in diverse contexts. One major limitation of the study was that most of the faculty members had not fully explored the potential of a recommender system, so collecting data and conveying the user interface concept was challenging. In addition, the concept of serendipity is very difficult to convey to faculty in terms of recommender systems and study materials search in an exploratory context. It takes a substantial amount of time to educate the recommender users for them to fully grasp the purpose of the study. Therefore, all of these limitations factored into creating just a glimpse into key user interface design consideration.

Future Research Directions

Along with faculty's perspectives, the student's (learner's) perspective is also necessary to explore the possibilities of user interface design studies. There is a vast potential for creating design patterns and user interaction frameworks to combine accuracy and serendipity in learning

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KEY TERMS AND DEFINITIONS

Context: Any information that can be used to characterize the situation of an entity.

Diversity: A recommendations list that covers a broader range of information increasing change of satisfying user information.

Novelty: It is related to serendipity which indicates an item new to the user and different to the user.

Transparency: It is the knowledge of a user about the working and functioning of the system.

Trust: The extent to which one is willing to depend on another entity in a specific situation.

APPENDIX

Table 7. Questionnaire

	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	I feel in control of telling the recommender what I want.					
2.	I don't feel in control of telling the system what I want.					
3.	I don't feel in control of specifying and changing my preferences (reverse scale).					
4.	I understood why the items were recommended to me.					
5.	The system helps me understand why the items were recommended to me					
6.	The system seems to control my decision process rather than me (reverse scale)					
7.	I found it easy to tell the system about my preferences.					
8.	It is easy to learn to tell the system what I like.					
9.	I found it easy to make the system recommend different things to me.					
10.	It is easy to train the system to update my preferences.					
11.	I found it easy to alter the outcome of the recommended items due to my preference changes.					
12.	The recommender can be trusted.					
13.	I was only provided with general recommendations.					
14.	The items recommended to me took my personal context requirements into consideration.					
15.	The recommendations are timely.					
16.	The recommender system helps me discover new products.					
17.	The items recommended to me are novel and interesting.*					
18.	The items recommended to me are diverse.*					
19.	The items recommended to me are similar to each other (reverse scale).*					
20.	The recommender provides an adequate way for me to express my preferences.					
21.	The recommender provides an adequate way for me to revise my preferences.					

PUBLICATION II

Transparency For Beyond-Accuracy Experiences: A Novel User Interface for Recommender Systems

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Transparency for Beyond Accuracy Experience

A Novel User Interface for Articles Recommending System

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Abstract

This paper reports about the impact of transparency of computation on the user experience of an interactive and serendipitous recommender system. We developed a user interface for JabRef (related work recommender) and Book Recommender system based on BookCrossing dataset. We further aided transparency of recommendation process in both the software. The recommender systems were made available for user evaluation. The experiment consisted of users in a university environment and they were of undergraduate level. Data was collected for subjective and objective evaluations.The analysis was used to determine the difference and impact of transparency on recommender systems where serendipity is frequently is used. The results showed that transparency has a positive impact on user experience, helps connection making during transparency and enhancing the trust of learners using it for learning purposes.

Keywords: Recommender Systems, User Interface, Serendipity, Exploration, Trust

1. Introduction

Learning technologies are changing the way education is imparted, the way learning material is used and consumed to produce an effective learning result [10]. As learning technologies are being used extensively, a recommender system is one potent game changer on the technological landscape[31]. Recommender System recommends items to the users, useful to their objectives. Recommender Systems have gained momentum in recent years [15,28,30,31,46,48,49]. As we progress the vision of research in recommender systems in the learning process, we aim transparency issues related to a recommender system. The recommender system when uses transparency increases trust among the users [8]. The main problem arises when the recommender generates serendipitous recommendations and user is faced with uncertainty. Serendipity oriented recommender system is required in learning to encourage exploration of new learning material, that is useful and not known to the learner before. As such system are used in learning, leaner's trust issues must be addressed. In our previous research, we were able to achieve serendipity by implementing user control in a recommender system. The serendipity slider and re-rank button user control were used to facilitate serendipity to users in the academic environment [2]. We further developed a context information tab for the user using this recommended to know about their situational (contextual information) update when using user control feature for serendipity. The contextual information update had a positive impact on user experience.

This research is based on the process of serendipity in digital environments by McCay-Peet et.al [32]. The author describes the process of serendipity as a trigger, delay, connection, follow-up, valuable outcome, un-expectedness and perception of serendipity. This research focuses on the internal and external factors of serendipity such as context that can be taken as something that highlights trigger and transparency that enables connection making. We have added transparency to the user interface designed for JabRef (An Open Source References Manager) and Book recommender system.

Our paper is divided into five sections. Section 2 covers related work on transparency and trust. We have discussed various definitions and dimensions to user trust, transparency and serendipity of the recommender system. Section 3 describes the experimental setup. We have focused on both user-centered study and data-centered study as mostly serendipity is subjective and measuring simply precision and recall cannot be used to measure the success of implementation. Also as most studies are accuracy oriented and driven by algorithms. Section 4 discusses the results and analyze the outcome of results. Section 5 discusses the implications of results on future of recommender systems.

II. Related Work

Our work for an academic recommender system is inspired by Bohemian Bookshelf [41]. We previously proved that rich user control and visualizations enable serendipitous encounters when seeking recommendations. Connection enabling is key for successful integration of serendipity in recommender system application in learning environments In addition to that it can potentially increase trust in the recommender system. As we know that serendipitous outcomes often have trust issues as they are “surprise” in nature. We therefore in reviewing the related work discuss some important milestone achieved in this domain and identify how it (Connection enabling and trust) can be improved.

We will be using terms such as Context, Transparency and Novelty, Diversity and Trust in the paper. These terms are defined as follows. Context is defined as "any information that can be used to characterize the situation of an entity [9] Transparency is defined "as the knowledge of user about the working of the system [43]". Novelty is related to serendipity, Novelty is defined as item new to the user and different to the user [23] Diversity is defined as a recommendations list that covers a broader range of information increasing change of satisfying user information [23]. Trust is defined as the extent to which one is willing to depend on another entity in a specific situation [22].

There have been various strategies for seeking serendipity and how to support it [38]. Stephan et.al defines “serendipity occurs when unexpected and aha moment of insight occurs ". The authors further explain that “It cannot be controlled but potentially be influenced." The authors believe that we cannot engineer serendipity but it can be facilitated and system engineers must focus on encouraging and incorporating elements of serendipity through digital technology. Further, they argue that in recent year’s recommender system has played a key role in attempting to work towards serendipitous information. As serendipity has gained momentum to being explored, it's important to observe other attributes of a recommender system. Two of the many attributes of recommender systems are transparency and trust.

Serendipity is defined as some instance of accidental and pleasing discoveries [7]. Serendipity for learning and scholarly activity has taken importance in recent years [3]. Serendipity is a need in academia as its needed to broaden their horizon and discover new areas of studies [39]. The main idea behind this activity is to produce interdisciplinary research. Some authors argue that one of the roles of libraries is to let users discover new content [7]. The occurrence of "happy accidents" is essential for discoveries that are followed by new developments. Author further stress that there is counter-narrative that students should be good searchers and not luck just students, the students should not only be prepared for serendipity by systems as well. Serendipity can be a source of an intellectual leap and new insights. Serendipity in recommender system has long been studied [1,2,12,14,25,47] . In most of these studies, the algorithmic approach has been applied to achieve serendipitous recommendations for users. As we know that serendipity is subjective and there is no formal agreement on the definition of serendipity but there are few that have helped to emerge a formal structure for the definition and studies. He et.al[20] have provided an elaborate view of Status of interactive recommender system being studied for serendipity. None of the systems achieve the serendipity via interactive or user control of the recommender system.

Transparency in recommender systems has been an area of interest of researchers for many years [44][17]. Transparency of a recommender system is needed to increase trust in the overall system. As literature shows visualizations have been used to make recommender system transparent; hence, making algorithms and their working mechanism visualize by graphs, diagrams, and colors. Denis et al [34] discussed control of the recommender systems. It involved the presentation of information through a Venn diagram by fusing information. The research advocates the idea of enhanced user experience due to context usage but argues that understanding contextual limitation is also important to recommendation processes. Denis Parra [34] studied various recommender systems visualization. The research can argue that transparency, contextual data and users traits are important factors. Verbert et.al. [44] Described the different dimensions of expert system visualizations such as exploration, transparency and user control. A recommender system talk explorer [44]was presented and studied for several parameters. It performed recommendation by inserting user's recommendation and enhancing the user's trust. Jesse Vig [45]discussed the recommendation using tags. The arguments based on the usage of, an intermediate entity for linking user and item relationship. Shuguang Han et.al. [17] Studied transparency and user control. He discussed controlling the recommendation process through topic relevance, candidate authority and social similarity in detail.

Moviexplain[40] is a movie recommender study for observing explanations with a recommender system. The research established that explanation of the recommender system is to enhance trust in the users. Trust is a key design concern and its fosters better understanding of the system [24]. In our research, this is especially important as during serendipity and context enabled operations user must know how the system is working. The current state of the art about transparency effects on trust in mixed. Some report positive and some report negative. Finally, the author argues not too little nor too much transparency can have a positive effect on users. Therefore our study can contribute to the current debate in the research. A study by Gedikli et.al [13]. The authors describe design guidelines for an explanation of the system. Some of the relevant design guidelines to our research are the first designer must increase transparency through explain for high user satisfaction. Second, there is a relationship between transparency and satisfaction. Four Reference models for transparency[21] study by Hossein et.al proposes four reference models for a baseline for transparent requirements for the information system. The models are meaningful transparency, using transparency, information quality, and transparency management. Transparency studies in recommender system have yet to conduct in references to these models. Therefore it's important that use transparency with useful and novel recommendations are investigated for testing these models. Trust in the recommender system has been studied in detail [8] [42] [35] [20]. Recommender system was designed as a tool assisting information overload or selectively filtering and suggesting user with information that is interesting to the user. But trust definition takes new definition as we are aiming at trust when recommender is not similarly an accuracy oriented recommender but serendipity oriented recommender. Further, serendipity has many types depending on the cause, route, and impact of surprise recommendation, therefore we trust establishment and maintenance in the recommender system becomes challenging. There are no formal studies in human-recommender trust in serendipitous recommenders. Trust in Context-aware computing has been done [16], therefore such studies can help us in designing trusted serendipitous recommender system.

Lim et.al[29] argues that users of contact aware system have great difficulty in reasoning about the system, thus rising trust issues. Decisions of the system are mostly not clear-cut to the users. The same issues are being studied in context-aware recommender systems. The authors consider trust as an integral part of the recommender system user experience. Trust has been studied in context-aware computing [46]. The main aim of trust factor studies in recommender system is that the recommender system is accepted by the users. This is especially important in learning domain where users are students, they have lesser experience of using such a system. Learners trust is an important factor in designing a recommender system as described by Fazeli et.al. [11]. The author discusses the degree to which teachers find online social activities useful. In this process, there are several activities that take place, such as sharing and recommending content, tagging, and rating, following, bookmarking, commenting and reporting content. These actions in the recommender system for learning show the relevance of learners control and issues related to them. We can infer that controllability in recommender system enhances the trustworthiness. We briefly present some studies for transparency, trust, and serendipity in a recommender system. The outcomes and impact of work can be mapped to our research and offers as a guideline for conducting the study.

Table.1: Outcome and Impact of Related Work

Study		Outcome	Impact
[16]	The Effect of Context-Aware Recommendations Customer Purchasing Behavior and Trust	Trust is the key User Control enhances more Trust	More User controlled recommender system to enhance trust issues with users in Learning
[27]	Trust Factors influencing the adoption of the internet-based inter-organizational system	Trust models are required for Internet-based organizations	E-Learning platforms need trust models for successful adoption in users.
[18]	Dynamics of Human Trust in Recommender System	1-Adjustment to human preferences us must for trust in recommender systems 2-Even if recommendations are not accurate, if its personalized users trust these recommendations	Recommender Systems in learning must adjust to learners/ students preferences
[6]	How to recommend? User Trust Factors in Movie Recommender System	Personalized Recommendations were mostly trusted	User-Centered Recommendations will be a success factor of future
[33]	The Serendipity Factor: Evaluating the Affordances of Digital Environments	Serendipity measured mostly in a specific digital environment	Opportunity for different subdomains of technology enhanced learning
[29]	Why and Why Not Explanations Improve the Intelligibility of Context-Aware Intelligent System	Users may not like receive to receive explanations all the time but on demand	User Controlled transparency can create a user-friendly experience in recommender systems
[40]	Movie Explain	Recommendations with justifications can increase recommender credibility and trust	Recommender sin learning sciences need accuracy and justification for credibility and trust
[26]	A survey of Serendipity in Recommender System	User interface based diversity oriented recommendations	Information exposure increase
[23]	Diversity, Serendipity, Novelty and converge	Beyond Accuracy, objectives are identified as critical recommender features	Serendipity and types of serendipity can impact user interface of recommender systems

Previous Work on User Controlled Recommender system [2] [4] shows that user control can be used to generate serendipitous recommendations for learning. Adding transparency in recommender system can make the system more trustworthy and learners can depend on it for study material recommendations [5]. This work is a continuation of previous work. In this work, we have added transparency tab to the recommender system (with Context tab) and compared it with the previous version of a recommender system that included a recommender interface along with the context tab.

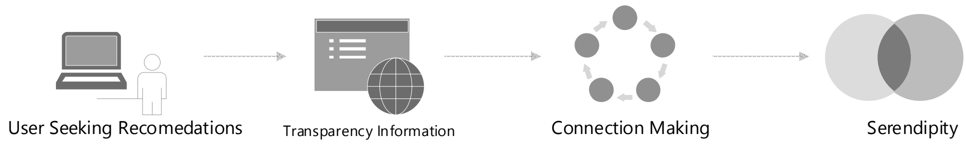

Figure1. Connection making through transparency for Serendipity

Transparency can not only make recommender system trustable but also help connection making for serendipity and also improve user experience when accuracy and serendipity is required by user. The dilemma of serendipity in recommender systems is that certainty during exploration of learning material the material might be useful later on, second the inclusion of serendipitous recommender in learning can be made easier when system is made transparent. Our contribution updates novel learning Resources, understanding of routes/techniques of Serendipity, forward and backward preferences revision and its implications while using recommended, learner trust in the system when serendipity in learning is not useful. The learner can understand the "un-expected route" to learning.

Problem Statement:

We aim to investigate that can connection making be enhanced using transparency as a key feature to the serendipitous recommender system. Second, this approach enhanced users (Leaners) trust in the system for usage in academic use.

III. Experimental Methods

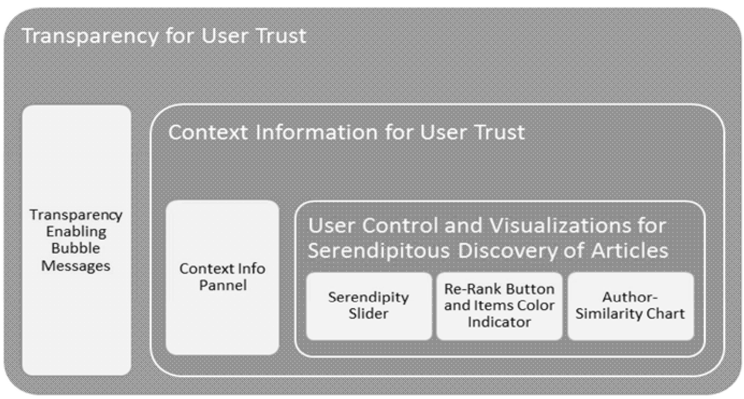

Figure. . Research Framework for Study on Transparency and Trust

The research approach is based on work done [37] and Afridi [2] by evaluation recommender systems on data centered evaluation and user-centered evaluation. We developed two versions of Recommender System. One version is called baseline and other advance recommender system. For both recommenders, we first evaluated recommender algorithms and apply the best possible algorithm for deployment. Then we distributed a questionnaire based on Pu. et.al for user-centric evaluation [36] of both recommender system. We performed multi vitiate analysis (MANOVA) on the data and Linear discriminate ant analysis (LDA) for observing differences and significance in attributes for two recommender systems.

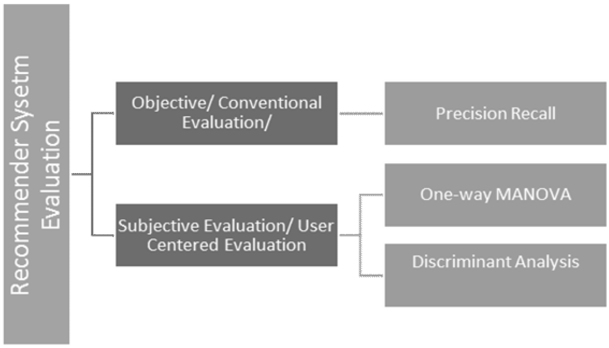

Figure.3 Date Centred and User Centred Evaluation

We formulated three hypotheses as given below:

Hypothesis 1: Transparency can facilitate connection making for a serendipitous experience

Hypothesis 2: Transparency has a positive impact on the serendipitous recommender system for learning

Hypothesis 3: Transparency can enhance user trust in a serendipitous recommender system

The Research Questions based on hypothesis are as follows:

Research Question 1: Does Transparency of Recommenders system facilitate connection making?

Research Question 2: How does Transparency impact user Experience for learning purpose?

Research Question 3: How does transparency impact user Trust for Serendipity Recommenders?

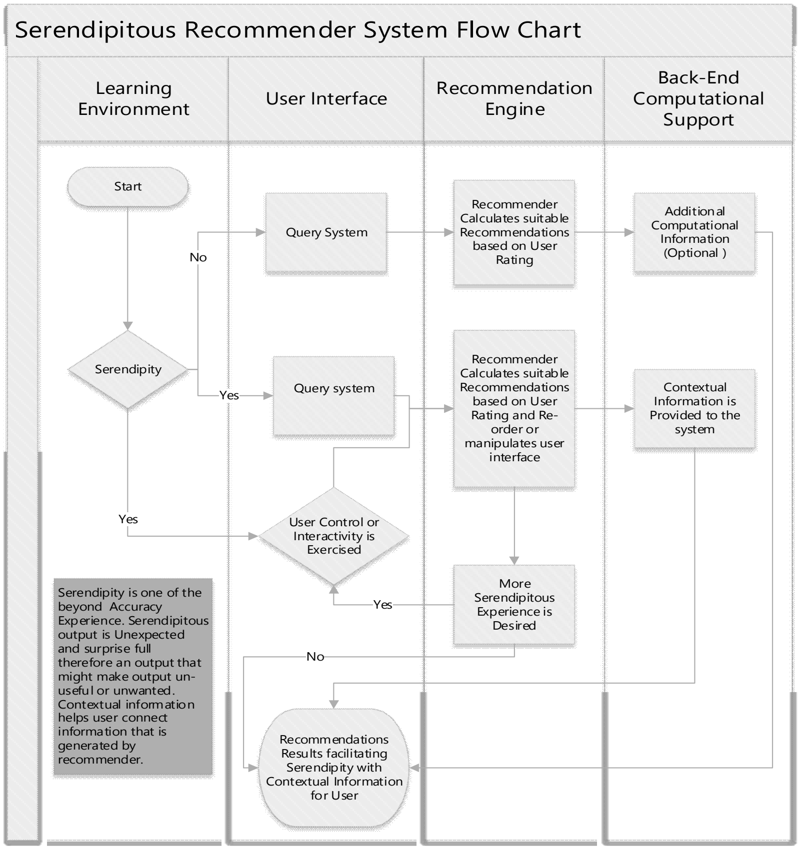

Figure.4: Workflow of Recommenders System Usage

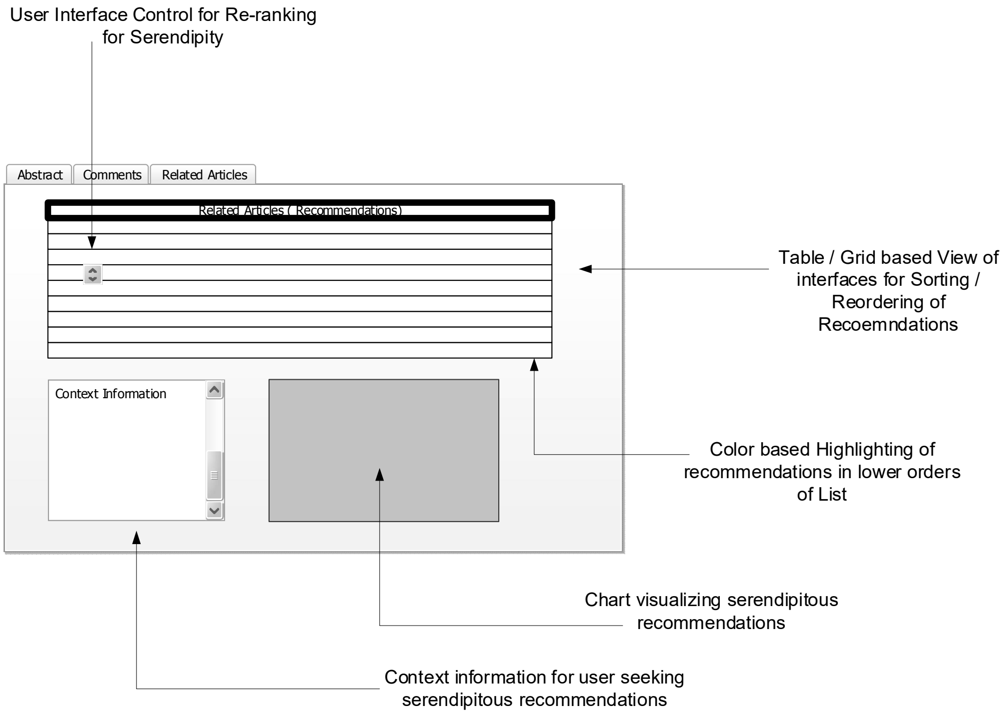

Figure.5. Design of Advanced User Interface for JabRef Related Work Tab

JabRef is an open source reference management software. The software received its recommendations form a backend recommendations service called Mr.DLib. The recommender sends the results to related article Tab. The open source nature of the project gives the opportunity to reach a large number of audience to test out the idea of user interface design for a recommender system facilitating serendipity. The recommender system works on the principle of accuracy orientation of recommending research articles to the user when clicked a particular article in the bibliographic library. We implement a new design, the features are as follows along with the narrative. Colors based prominence and table controls will facilitate a near-by effect of serendipity. Researcher and similarity scatterplot will facilitate user to look for authors where potential serendipity can take place. Explanation of various menus will add up to the transparent layer of the recommender system user interface.
Our philosophy of user experience in our new user interface is an explanation of the following mechanism.

1. Explanation of Author centered school of thought highlighting
2. Explanation of Paper-author similarity table
3. Explanation of Recommendations and Serendipity Process

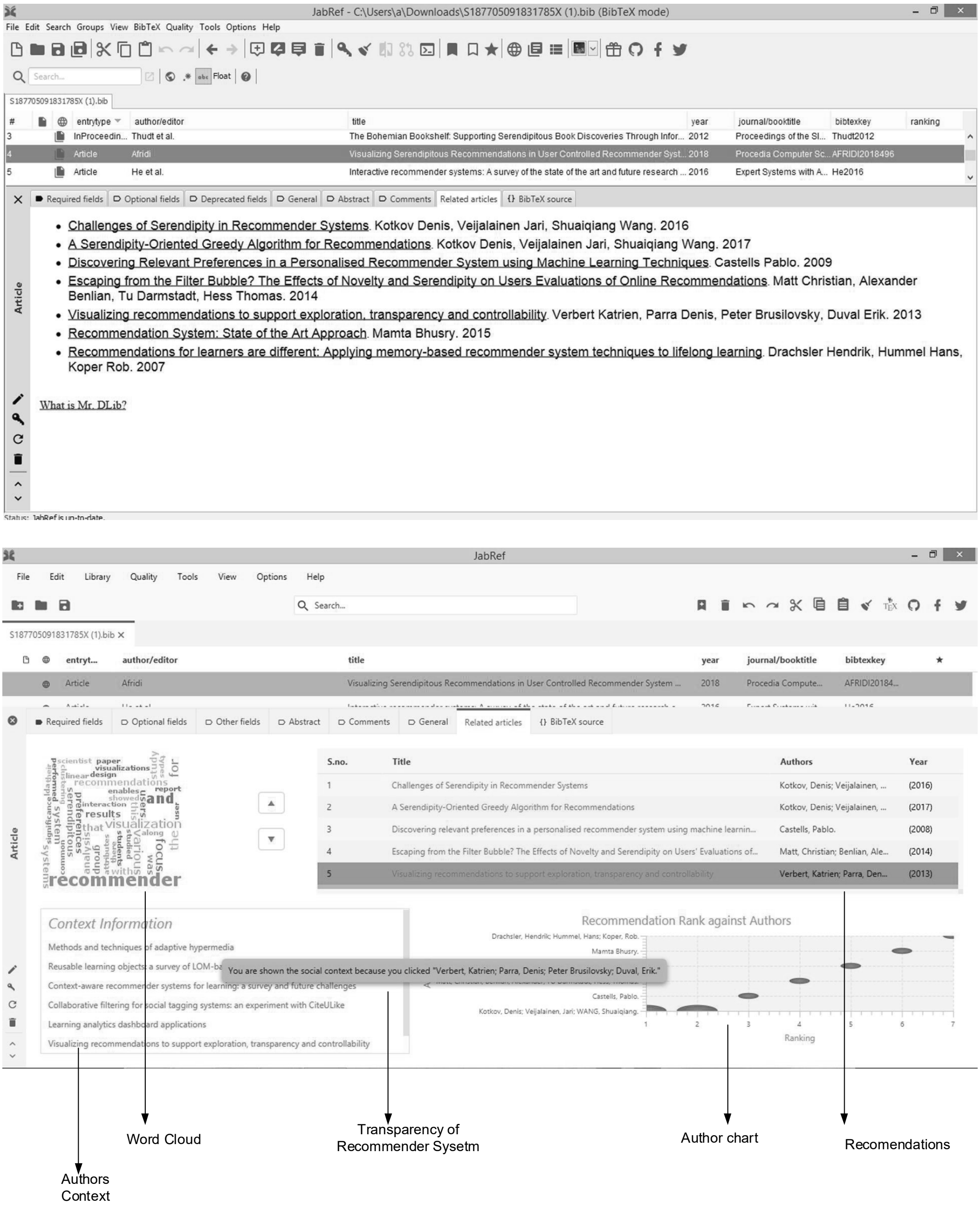

Figure .6. Standard and Advanced User Interface of JabRef

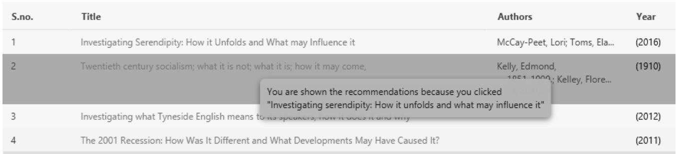

Figure.7 Explantion of Recommendation Process

Figure.8 Explanation of Author Citation Chart

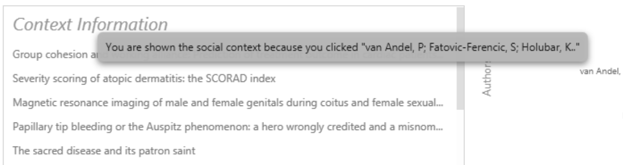

Figure.8 Explanaiton of Acedemic Context Information

Figure.9 Frequently used Word Cloud in Selected Paper

Evaluation Results

The evaluation results of 43 students at bachelors and masters levels is given below. They were shown, explained and encouraged to user the software. The Data was collected in the form of questionnaire and processed in SPSS. The Results for user experience was calculated through discriminant analysis. The results are given below.

Table. 3 Multivariate Analysis for Subjective Evaluation of Interfaces

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.985	549.537[b]	9.000	76.000	.000
	Wilks' Lambda	.015	549.537[b]	9.000	76.000	.000
	Hotelling's Trace	65.077	549.537[b]	9.000	76.000	.000
	Roy's Largest Root	65.077	549.537[b]	9.000	76.000	.000
System	Pillai's Trace	.635	14.714[b]	9.000	76.000	.000
	Wilks' Lambda	.365	14.714[b]	9.000	76.000	.000
	Hotelling's Trace	1.742	14.714[b]	9.000	76.000	.000
	Roy's Largest Root	1.742	14.714[b]	9.000	76.000	.000

a. Design: Intercept + System

b. Exact statistic

Table.4. Wilki's Lambda

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.365	80.204	9	.000

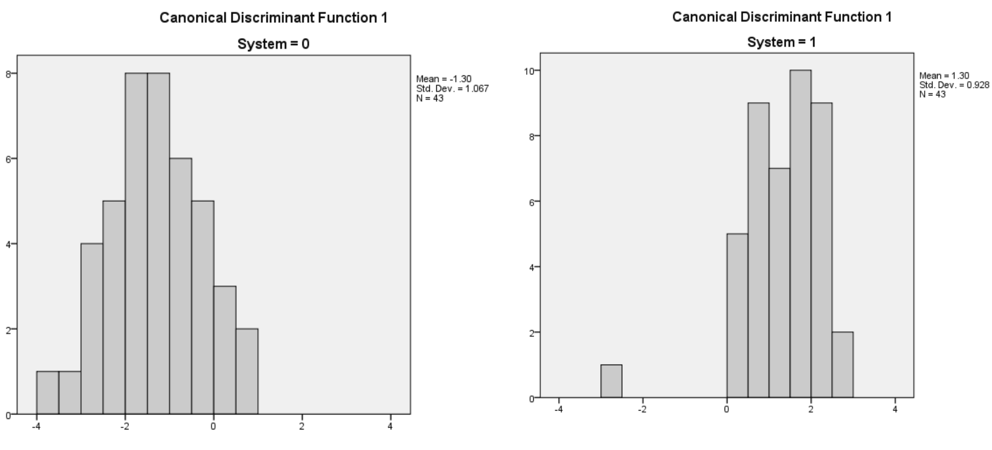

Figure. 10. User Experience of two recommenders interfaces

The results show that there is a significant difference in the user experience of related work tab (recommendation) of baseline and advance use interface implementation.

Experiment No.2

The second experiment is designed to evaluate a low-user controlled enabled recommender system with transparency tab for leaners. The transparency tab shows contextual transparency to the user for connection enabling. The tab has minimal to No visualization except the table. There is minimal or no playfulness and lease multiple entry points. The table based text boxes highlight adjacency emphasis and Text-based Transparency. The recommender is based on bookcrossing dataset. The design layout of the recommender systems given below in figure 6.

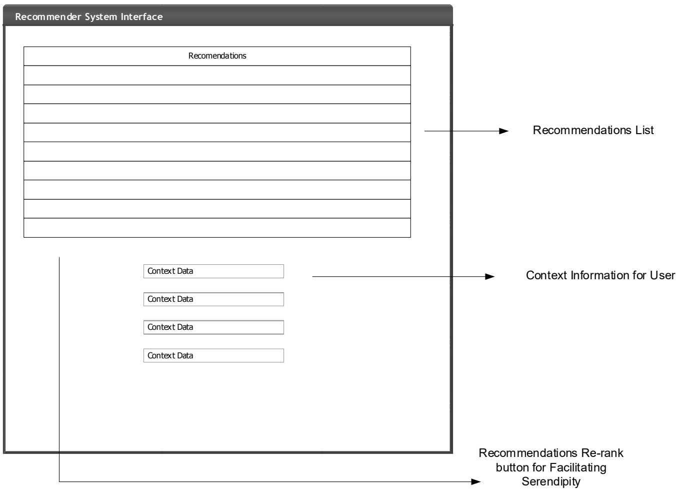

Figure. 11. Design Layout for light User interface for Serendipity

Table. 5: Recommender System Evaluation

Recommender Class	Item Similarity Recommender
Similarity Type	Jaccard
Training Method	Auto
Mean Precision	0.260
Mean Recall	0.094
Threshold	0.001
Dataset	BX BookCrossing
Recommenders Algorithms Evaluation	Precision and Recall
Framework chosen Baseline Algorithm:	Popularity based Recommendation
Reason for Automatic Choice:	Dataset

Methods

We applied data centered and user-centered evaluation to measure if our proposed workflow has a positive user experience. As part of both experiments, we developed a recommender system in Graphlab machine learning framework. The Graphlab automatically selects a most suitable algorithm based on the underlying dataset. In this case, we used Movielense data set has been used. The Graphlab automatically builds a baseline algorithm for providing a relative comparison. In this case, the recommender has developed Popularity based recommender algorithm as a baseline. Both of the Precision and Recall values have been shown in the figure. The context tab and transparency tab was developed in .NET framework. Both tabs simulated the context and transparency information for users using a recommender system. The context tab displayed information such as user location, library status, and serendipity revision option. The transparency tab provides an explanation to all the context information providers in the form of text boxes. The user interacts with both of these tabs for advance recommender evaluation and only with context tab when using recommender system serendipity features when evaluating baseline.

Data Centred Evaluation

The figures provide the user interface of a recommender system, the context tab and transparency tab developed for the experiment.

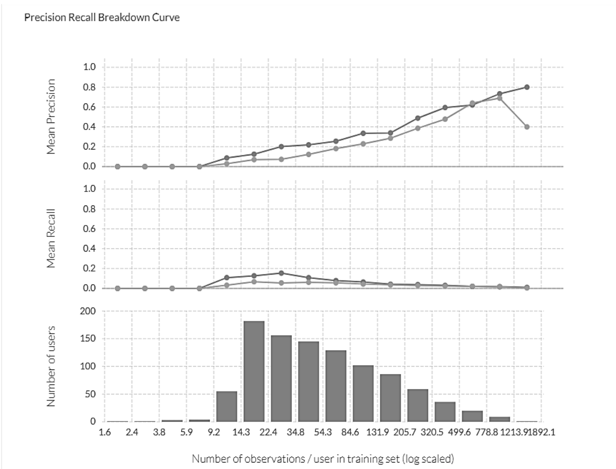

Figure. 1 Recommender System Developed in Graphlab

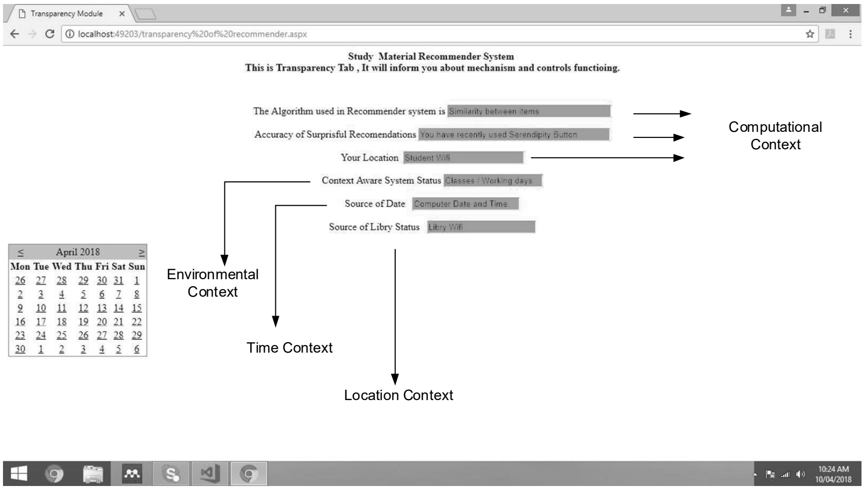

Figure. 13 Transparency Information

User Centred Evaluation

The user-centered evaluation consisted of the focus group (60 users) of undergraduate level students. We distributed 6 questions for both baselines and advance recommender system. We calculated the generalized multivariate model Multivariate analysis (MVA) and Linear discriminant analysis (LDA) in SPSS 20. The data was collected for 57 users. Three users did not respond. The user answered a questionnaire for context enabled recommender system and transparent context-aware recommender system. The recommender system was developed in Graphlab python framework. The Movielense [19] dataset was used for setup recommender system. The Recommender system was enabled with the re-rank button of recommendations and slider (to increase or decrease recommendations list) to generated serendipitous recommendations. Further users were then shown advance recommender system with baseline features of all baseline system but addition transparency tab for context information tab. The users clicked to see the prototype contextual tab and transparency tab explain the context data. Further, the student discussed the various option of recommender system user control and possible learning scenarios. In our analysis the baseline recommender system represented by 0 and advance recommender system by 1. The questionnaire is based on Pu et.al [36] work for user-centered evaluation. This methodology has been adopted by Afridi [2] and Vegt et.al [37] for users centered evaluations.

Table.6. Questionnaire for Users in User-Centered Evaluation

Questions
The recommendations are Useful for me
The items recommend to me tool my personal context requirements into consideration
The recommendations provide me with novel information
The recommendations are surprising to me
I feel in control of telling recommender what I want

The recommender can be trusted

IV Results

The following table shows results from multivariate analyses is based on MANOVA. Two (2) independent and six (6) dependent have were used. The data set was collected in Likert Scale from 1 to 5. 1 for strongly disagree Up to 5 for Strongly Agree. Multivariate and Linear Discriminant Analysis showed significance (P<0.001) for various tests. Further significance value (P<0.001) for Wilki's Lambda showed that there is there is a difference of user experience in both the recommender system. The canonical discriminant function values for baseline recommender (0) and advances recommender (1) is shown in the figure. The results show that overall user experience improved with transparency tab added to context information enabled recommender system. It's important to note that the serendipity effect of recommendations and context information requirement of the recommender.

The evaluation of Recommender System was done for attributes of a recommender system such as usefulness, context, novelty, surprise (serendipity), control and trust. We observe that along the lines of these attributes, the advance recommender system with its transparency tab does have a positive impact on user experience. As all of these attributes show s significance in the multivariate analysis and tests between subjects. The canonical discriminant functions in the figure show the positive shift of user experience for advance recommender system. The results show a trust as a factor creating a positive experience on the user. A trustable recommender system is even more important when the user is exercising serendipity oriented recommendations. As earlier, we have discussed that serendipity often causes confusion or disarray because the output is not required from the system. User control and context and transparency is the personalization of the recommender system.

Table.7. Multivariate Tests

Effect	Value	F	Hypothesis df	Error df	Sig.
Pillai's Trace	.984	1101.413[a]	6.000	105.000	.000
Wilks' Lambda	.016	1101.413[a]	6.000	105.000	.000
Hotelling's Trace	62.938	1101.413[a]	6.000	105.000	.000
Roy's Largest Root	62.938	1101.413[a]	6.000	105.000	.000
Pillai's Trace	.305	7.665[a]	6.000	105.000	.000
Wilks' Lambda	.695	7.665[a]	6.000	105.000	.000
Hotelling's Trace	.438	7.665[a]	6.000	105.000	.000
Roy's Largest Root	.438	7.665[a]	6.000	105.000	.000

a. Exact statistic

b. Design: Intercept + system

Table.8. Box's M Test Results

Box's M		52.443
F	Approx.	2.352
	df1	21
	df2	44503.780
	Sig.	.000
Tests the null hypothesis of equal population covariance matrices.		

Table.9. Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.695	38.868	6	.000

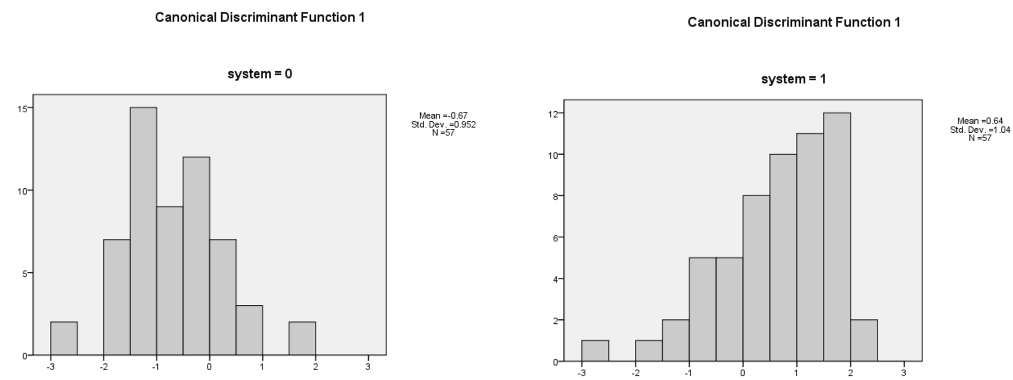

Figure.14: Baseline and Advance Book Recommender System User Experience

V. Conclusion and Future Research Direction

The experimental results show that transparency of recommender system enhances the learner's trust on recommender system during serendipity oriented recommendations generation by learners. The results also proved that the explanation improves the connection making process and hence enhanced learner's experience. The experimental results prove that the serendipity can benefit the user if there is more emphasis on the transparency of the recommender system helping the user in the decision process.

In learning sciences and technology, serendipity oriented recommendations especially that are trustable are even more required. We use serendipity oriented recommendation to discover new learning material, explore various options in academic resources, build a new understanding of the subject by revising learning material form same author or different authors, keeping in mind the usefulness of recommendations. Further, the serendipity of recommendations can help user stumble upon learning material that might be so interesting to the user that it might become part of the permanent course of learning. Since there not many case studies on serendipity, especially in learning, therefore it's imperative to develop more user studies in order to understand the output of such recommender system, outcome, and impact from implementing such technologies. Finding from these studies can be helpful in other domain such as Netflix recommendations for movies, Google apps, and apple app store. It can also change the online learning course platforms such as Course and Edx.

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PUBLICATION III

Facilitating Research Through Serendipity of Recommendations

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ORIGINAL RESEARCH

Facilitating research through serendipity of recommendations

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Abstract
Recommender systems are used to suggest items that are useful to users. The recommendations can be surprising and may be categorized as serendipitous recommendations. One of the limitations with serendipitous recommendations is that the user interface of such a recommender system rarely supports the user to switch from accuracy orientation to serendipity facilitations. Using serendipitous recommendations can be challenging. This is because the user might not fully benefit from and understand the serendipitous recommendations. One main advantage of this type of system is that a serendipity-oriented recommender system can be used for the supervision of research students. It can help them to find a novel topic in the area of their research interests. This paper reports on a novel user interface design for facilitating serendipitous recommendations generation in educational environments. The user interface of this recommender system provides students with user controls and visualization in order to explore research articles. This research comprises user experience experiments conducted in an academic environment and evaluated by means of a user centered design evaluation. It involves research articles recommender system named JabRef. The recommender systems were used by students at the undergraduate level. Users reported an enhanced user experience while using the user controls and visualization and serendipitous resource discovery. It was found that user interface design can facilitate a serendipity recommender system in the learning environment. University professors supervising students during the research can also benefit from the recommender system.

Keywords Serendipity · Transparency · User interface · Recommender system

1 Introduction

Recommender systems in higher education have been extensively researched and studied for their potential for enhancing outcomes by improving the educational activities (Drachsler et al. 2015; Kaklauskas et al. 2013; Lu et al. 2015; Verbert et al. 2007). Recommendations are generally similar to subject recommendations, learning resource recommendation and books recommendations, and different learning activities/modes recommendations, such as meetings and conferences. Serendipity capability in recommender system was achieved through algorithms (Chiu et al. 2011; de Gemmis et al. 2015; Kim et al. 2017; Kotkov et al. 2016; Murakami et al. 2008; Xiao et al. 2014). In previous work (Afridi 2018a, b, c, 2019a, b), Afridi presented his work on user-controlled serendipitous recommenders for learning. Recommender system and literature exploration have attracted the interests of various researchers (McKay et al. 2015; Thudt et al. 2015). User interface design specifically oriented toward this kind of mission has encouraged the emergence of new recommender system user interfaces (Bruns et al. 2015). Information systems have long been used to facilitate serendipity (Mark et al. 2013), and even augmented reality systems are also reported to facilitate serendipity as well (Bach et al. 2017). User interface design for information systems is motivated by the exploration of a novel material for users (Pang et al. 2015). Consider a scenario in an academic institution: Ahmad, a university student, is looking for a research topic in the area of his interest. He meets with a research supervisor for guidance

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and to explore new research areas. The research supervisor suggests some articles that are related to the supervisor's research group's interests, but they are new and unexplored. The supervisor asks Ahmad to look for himself for topics that seem interesting and surprisingly new to work on. After doing so, Ahmad selects some papers and explores the authors' profiles to find direction and make connections in the scholarship.

Our work on research articles recommender system user interface is inspired by Bohemian Bookshelf, the work of Thudt et al. (2012). The Bohemian Bookshelf design strategy revolves around the model of a library of a library, offering a visualization that facilitates discovery in a context similar to a bookstore or library. The factors that authors consider for serendipity are personality traits, observation skills, open-mindedness, knowledge, preservice, and environmental factors such as coincidence and systems. The author establishes design principles for its visualization, encouraging serendipity through multipoint entry, juxtaposition of information, playfulness, and flexibility of exploration of visualization. This work is relevant to us as it provides a state-of-the-art baseline for the development of our serendipity-facilitating user interface. Furthermore, as we work in the digital library, there is a need for understanding the academic search and information seeking models. This work provides us with design guidelines for research articles that explore facilitating serendipity, as shown in Fig. 1. However, Bohemian Bookshelf design principles do not answer some of the challenges that we face when designing the user interface for the research articles exploration. First, there are no title pages or book covers for research articles. Second, the papers are, more or less, roughly the same size for conferences and journals. Third, the researchers often look for authors who are working in the same area as they are, so authors are known from their work portfolio. Therefore, it is important to offer a visualization to users, helping them find related authors, in order to spark serendipity.

In our research, the Bohemian Bookshelf design principles are applicable. Two experiments have been designed to explore how interactivity can be helpful in facilitating serendipitous recommendations. Furthermore, we want to explore the impact and usefulness of various user interface

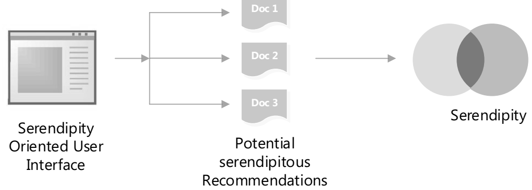

Fig. 1 User interface facilitating serendipity

visualization and user controls. Using serendipity in learning environments is imperative if a new route to learning is required. The recommender system can be interactive (user-control serendipity) and can offer freedom of choice to the leaner. It may not interfere with traditional learning and it can facilitate surprising recommendations when they are needed by learners. Learners decide the timing and the need for surprise recommendations and interactivity can help when recommended study material becomes irrelevant. One of the major motivating factors to conduct this study is the need to develop a real-world study of research article recommendations that benefit from serendipity. This work is a step toward user-controlled and visualizations-driven serendipitous discovery of useful recommendations. This study will enable us to further study factors that influence the learner's serendipity endeavor. This paper contributes to a theory of visualization development for serendipity-oriented recommendations and makes a contribution to open-source software. The contributions can be validated in a variety of learning environments and can be applied to non-academic environments as well.

2 Related work

In the twenty-first century, learning will be done through technology enhanced learning. The pervasiveness of ICT infrastructure has encouraged technology enhanced learning in education sector. Higher education colleges and universities are also availing maximum benefit of this paradigm shift. One of the technologies used for enhancing the learning process is recommender system. Recommender systems research has attracted interest over the years (Jiang et al. 2018; Mashal et al. 2016; Park 2019; Pla Karidi et al. 2018; Yang et al. 2018). Recommender systems are software systems used to recommend learners about learning resource, process choices, and information filtering due to information overload. We are interested in maximizing learner's performance. With the passing times, recommender systems are going through evolution; more and more features are added to fit the user's needs.

In the field of technology enhanced learning, recommender system research has been studied for over 10 years (Beel et al. 2013, 2015; Drachsler 2011; Verbert et al. 2012). Recommender systems are generally acting to predict users' choices based on past behaviour. There are many definitions of recommender system (Drachsler et al. 2010; Ekstrand et al. 2015; Verbert et al. 2007). In this work, we will consider the definition of recommender system by Melville and Sindhwani (2010) as "a system that generate meaningful recommendations to users for items and products". Recommender systems are the instruments that can help the learners in their learning progress. Recent years have seen an exponential growth of recommender systems used in educational and learning environments. Recommender systems help learners; in a proactive manner, based on past behaviour and profile information, suggest books, websites, movies or suggestions based on learner's performance in a test or problem-solving exercise.

Recommender systems are accuracy oriented. We are aiming towards developing serendipity-oriented recommender system. The serendipity will be introduced via user control of recommender system. As user generates serendipitous recommendation, the user might need contextual information and transparency in order to better understand the situations when it uses serendipity feature. A context tab and transparency tab will be added to study the trust in overall experience of recommender system. Although there is a lot of research around recommender systems, the effect of user control in recommender systems still need exploration as it can provide plenty of opportunities for learning. In this research, we want to further explore the following aspect of user control for context-based recommender systems in learning.

- Exploring human intervention on the outcomes of an algorithm.
- Enabling self-directed learning processes of learners by enabling the orchestration of recommender features to our needs.
- Enhancement of learner's serendipity experience enabling user control without affecting learning goal.
- Enhancing the educational impact of recommender system based on user needs.

There seems to be a positive relationship between user satisfaction and user control of a recommender system (Parra and Brusilovsky 2015). When mentioning user control in recommender systems, two major kinds of user control are considered, namely: functional control and structural control over recommender systems. The functional control of recommender system aims to change the behaviour of a recommender system, adjusting or customizing to specific needs of the user (Harper et al. 2015). Structural control aims to change the structure of recommender system by enabling or disabling a complete module; hence, changing the 'structural control' of a recommender system can have a major difference in the behaviour and performance of recommend system (Ekstrand et al. 2015). Learners are constantly getting accuracy-oriented recommendations, and they are faced with loop or bubble affect called over specialization. In order to receive diverse but useful recommendation which can be surprising, the recommender has to generate recommendations called serendipitous recommendation.

Recommender systems in learning have been designed to align with traditional learning. In a traditional learning environment, learners progress on a fixed roadmap or course. They follow a particular route or course outline to achieve a learning outcome. It is a step-by-step process and recommenders aiding such processes are limited to the course contents. Serendipity has been researched to observe new experiences in recommender systems as discussed by He et al. (2016). Thus, there is a need for having user control for two aspects of recommender systems. The recommender system must be relevant to the user and should recommend new and interesting recommendations to the user. There is existing literature on serendipity and its environment, as discussed by McCay-Peet et al. (2015), we will follow Makasai's definition of serendipity as "the quality of being both unexpected and useful" Maksai et al. (2015). By this definition, we are focusing on relevance and unexpectedness. Further evaluating the concept will involve the user and data-centric evaluations. The generic interaction model presented by Pu et al. (2012) showed three elements in which user interaction is necessary for recommender system behavior: first, the preference elicitation; second, the display of recommendations; and third, a revision of preference. The framework discusses a user-centric evaluation rather than an algorithmic-centric evaluation of recommender system. The outcome is a designed guideline for a serendipitous recommender system. Literature reporting serendipity-facilitating interface are shown in Table 1.

Serendip by Alexander et al. (2015) has been critical and informed our approach by fostering serendipitous information-seeking. The main idea for the work is to utilize a broader view of the entire corpus. This approach lets users adopt the best route to the serendipitous resource discovery. Similarly, Rädle et al. (2012) discussed a collaborate visualization search that promotes serendipitous book discovery in book repositories. Information visualization as presented in VizBiz by (Zhang and Seifi n.d.) supports the idea of rich user search facility. Calero Valdez et al. (2015) presented a novel visualization technique that helps harness a knowledge management application to facilitate serendipity by developing visual recommender system. Keywords and authors' information have been used as key elements in the visualization. Serendipitous browsing has been discussed by Kleiner in research titled "Blended Shelf" (Kleiner et al. 2013). The research shows that 3D presentation of the library can be helpful in presenting the serendipitous search facility to users. Hinrichs et al. (2016) discussed the information visualization that helps the exploration of literature. The work uses visualization techniques to explore short science fiction stories by using keyword cloud and timeline views.

Maxwell et al. (2012) presented a semantic sketchbook facilitating reflection for supporting serendipity. The work is supported by prototypes and is grounded by evaluations for serendipitous outcomes. Artz by Dumas et al. (2014) presents an exploration of artwork by developing a visualizing

Table 1 Literature reporting serendipity-facilitating interface

Study	Outcome	Impact
Alexander et al. (2015)	Serendipity can be facilitated by visualization	Novel items exploration techniques through serendipitous system
Rädle et al. (2012)	Serendipitous book discovery system facilitated via visualization	New route to learning through information visualization facilitating serendipity
Zhang and Seifi (n.d.)	User control can facilitate item discovery	Serendipity and accuracy perspective of user interface design needs to be considered when implementing user control
Calero Valdez et al. (2015)	Visual trigger for serendipity can facilitate serendipitous encounters	Novel technique for exploration-centered literature search can be harnessed
Blended shelf Kleiner et al. (2013)	Exploration-facilitating visitations	New interaction techniques for libraries and educational digital spaces
Dumas et al. (2014)	Visualizing art system that help discovery of complex items	Exploration of beyond-explainable items, suitable for science as well
Cleverley and Burnett (2015)	Serendipity facilitation via color of output	Exploiting colors for user attention for serendipity

technique. It helps users experience serendipity. The interface offers browsing, analysis, and exploration options that allow the user to have a playful interaction. Cleverley and Burnett (2015) presented their work on serendipity, advocating that serendipity can be facilitated via certain user interface design factors such as color. Mark et al. (2013) described how triggers and connection-making are important elements in the serendipity process. One of the triggers includes a visual trigger. The connection is facilitated by a prepared mind. Our approach of redesigning a user interface is an attempt to develop new visual triggers and connection-making in an academic environment. Serendipity has been investigated for teachers in higher education (Afridi 2019a)

The literature reveals the following points when we combine the recommender system serendipitous behaviour with novel user interface design.

- Recommender system benefit from both users controlled and automatic feature of the system.
- Serendipitous recommendations can be enhanced via rich visualizations and controls.
- Transparency and serendipity both benefit each other in presenting recommendations to the users.
- Educational and learning sciences still need more case studies for proving serendipity-oriented recommender systems.

3 Research approach

We used a new user interface for JabRef reference management software recommender system as our testbed prototype. We already tested some concepts such as transparency and user control for serendipity facilitating recommender system (Afridi 2018c, 2019b). Our prototype provides three design advantages. First, facilitating visual triggers, second visualizing serendipity of recommendations vs accuracy of recommendations and third facilitating learners in finding surprising literature. The recommender, based on the selected items, searches for a list of suggestions by a backend system. The recommendations are returned based on the similarity index and presented to the user according to it. The re-ranking/reordering can bring a most unlikely or surprising result to the user, facilitating a serendipitous experience. This presentation can be made even more reliable by presenting the similarity score with the items or items numbering. The recommendations can be further aided with contextual information or transparency of information in order to facilitate the serendipity process.

(RQ1) Can serendipity be useful in suggesting novel and useful items (research articles) to students?
(RQ2) Does interactive recommender serendipity facilitation helps users (learners) in research activities?

The following hypotheses were tested in the experiment.

(H1) Serendipity-oriented user interfaces of recommender systems can help students find useful and novel items (research articles).
(H2) Serendipity facilitating interactive recommender system helps users in research supervision.

We evaluated our approach by implementing user-controlled serendipity facilitating recommender interface in the learning environment as done in Erdt et al. (2015) and Knijnenburg and Willemsen (2015). We tested our recommender in a user-based evaluation based on Pu and Chen (2010) and Pu et al. (2012). The evaluation process consisted of data-centered and user-centered evaluation stages.

Data-centered evaluations were issued by precision-recall studies of algorithms chosen by the recommender system development framework. The user-centered evaluation consisted of user data collection about the serendipitous experience. Questionnaires were distributed in focus groups of 57 users and assessments were made on the usefulness of our approach at the Institute of Management Sciences, Peshawar. The user-centered survey involved questions for the user to evaluate the performance of the baseline and user-control-driven serendipity. The following questionnaire was distributed to the students. A Likert scale was used to record responses from students. The scale used ranged from 1 to 5, with 1 representing strong disagreement and 5 representing strong agreement. The questionnaire is reproduced below. The design of user interface is presented in Fig. 2. Most recommender systems are evaluated from 20 to 100 user evaluation (Shani and Gunawardana 2011).

1. The recommendations are relevant to my activities
2. The recommendations are surprising to me
3. The recommendations differ significantly from each other
4. The recommendations are useful to me
5. I am satisfied with the language of recommendations
6. The recommendations provide me with novel information

We developed a questionnaire based on Pu et al. (2012) and Pu and Chen (2010) to survey the recommender system users about their experiences. This questionnaire was more detailed and focused more on the impact of recommender system on academic system and studies experiences. The questionnaire is reproduced below

1. I feel in control of telling the recommender what I want.
2. The system helps me understand why the items were recommended to me.
3. I feel supported to find what I like with the help of the recommender.
4. I quickly became productive with the recommender.
5. The layout of the recommender interface is attractive and Adequate*.
6. The recommender explains why the products are recommended to me.
7. The items recommended to me took my personal context requirements into consideration.
8. The items recommended to me are novel and interesting.
9. The recommender can be trusted.
10. I prefer to use this type of recommender in the future.
11. The recommender made me more confident about my selection/decision.
12. The recommender system is educational.
13. The items recommended to me are novel and interesting*.
14. If a recommender such as this exists, I will use it to find Research articles.

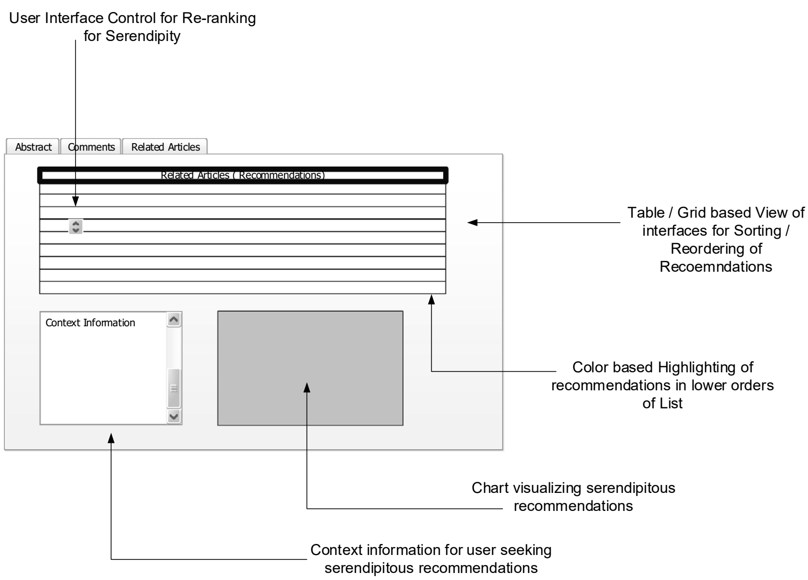

Fig. 2 Design layout for recommender system user interface

4 Experiment

The related articles tab shown in Fig. 5 shows that related work once a user clicks on a reference in the bibliographic list. The returned list is a response from a backend recommender system called Mr. DLib (Beel et al. 2011), a service that offers recommendation-as-a-service. The basic idea for changing the user interface to a serendipity-facilitating recommender system is to help the researcher find surprising and useful research papers. For example, Mahad, a university student is looking for some new topics in recommender system user interface, might use the user interface for related work tab with standard features. He would enter the bibliographic references to the JabRef library. Upon clicking the bibliography, the JabRef related work tab returns 5–7 recommendations. The author similarity chart shows how similar or different one author's work is to another. Works by similar authors are represented by points on the same level as the chart. The flow of function while operating the recommender system is shown in Fig. 3.

Researchers look for authors whose work is similar to their own. For students, searching for a similar author can help them to focus on important work and look for specific topics. Normally, authors have profiles on major academic servers such as Google Scholar, ACM, and Elsevier. Because researchers normally work on specific research interests, it is important to spark serendipity when the user is able to see which authors are working on similar topics that are close to their own research interests. The recommender system Mr. DLib returns a list of recommendations when a user clicks on a specific article. The scatter plot chart depends upon the number of authors and similarity index returned by the recommender engine (Mr. DLib). The scatter plot chart is not interactive, but it can be upgraded to convey internal information for a recommender system. Default version of user interface is shown in Fig. 4, and the user interface is shown in Fig. 5.

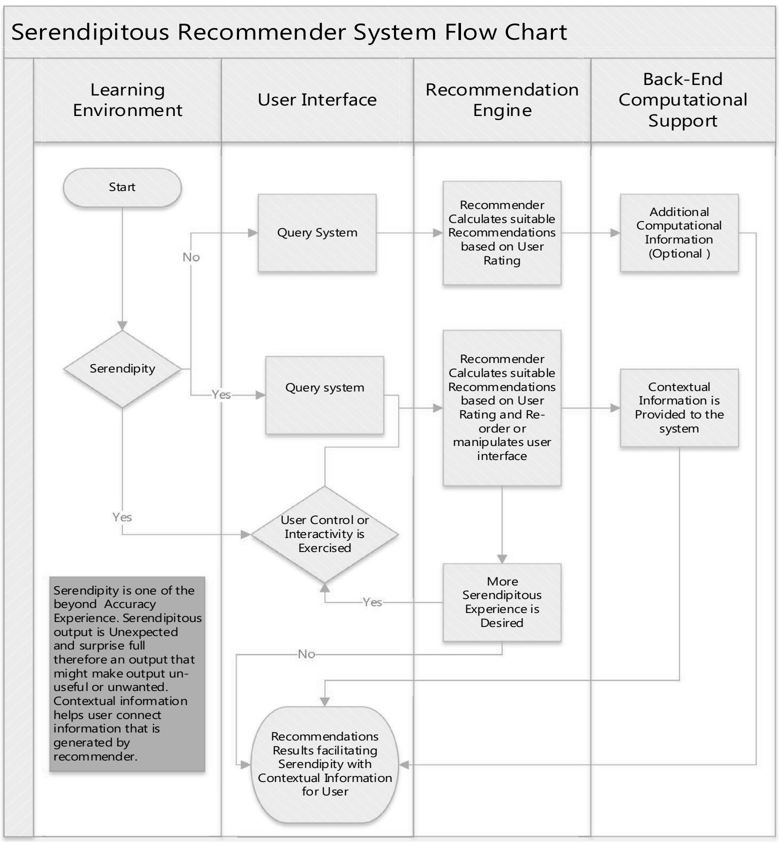

Fig. 3 Flowchart of recommender system user interface interaction

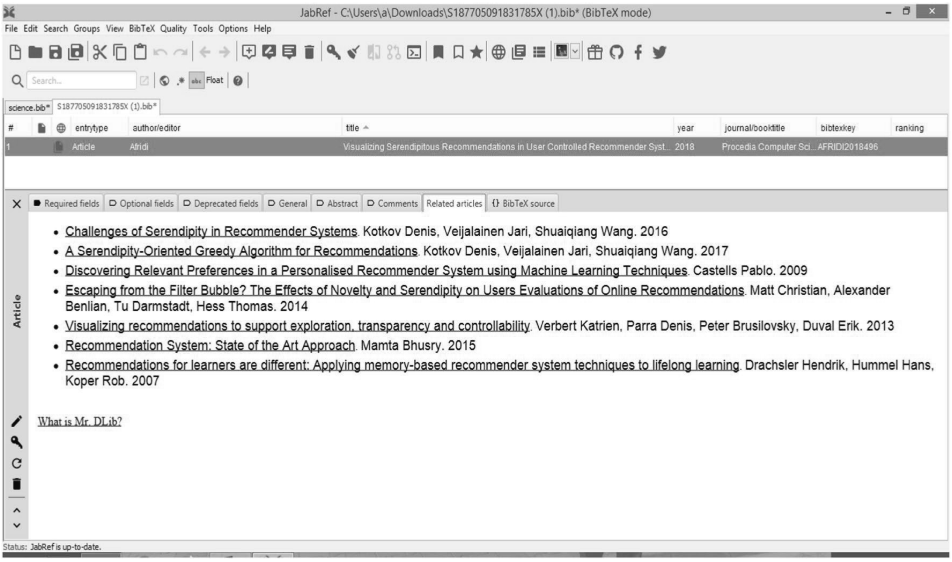

Fig. 4 JabRef related articles (recommender) original user interface

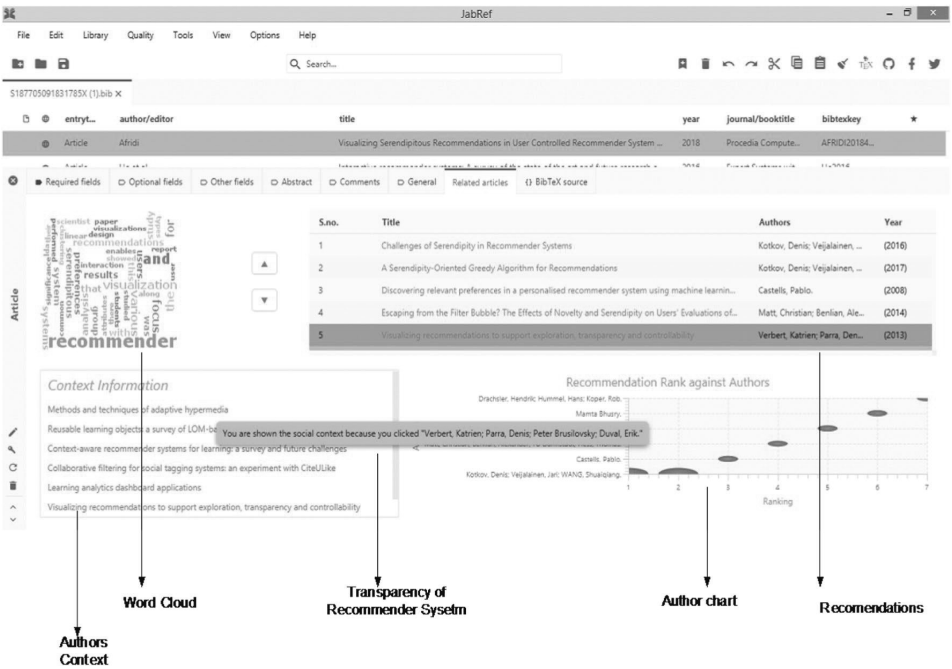

Fig. 5 New user interface for article recommendations for JabRef

Table 2 Tests of equality of group means

	Wilks' lambda	F	df1	df2	Sig.
Relevance	0.862	17.750	1	111	0.000
Serendipity	0.537	95.619	1	111	0.000
Difference	0.939	7.214	1	111	0.008
Useful	0.841	20.916	1	111	0.000
Language	0.805	26.878	1	111	0.000
Novelty	0.717	43.870	1	111	0.000

Table 3 Eigen values

Function	Eigen value	(%) of Variance	Cumulative (%)	Canonical correlation
1	1.213[a]	100.0	100.0	0.740

[a]First 1 canonical discriminant functions were used in the analysis

The Re-rank buttons are used for re-ranking recommendations. The idea for using the control is to allow the user to explore through recommendations by re-ordering/re-ranking. Both controls help highlight the adjacency of accurate recommendations. The results returned in the table highlight the potential of serendipity recommendations through colors. Previous work suggests that serendipitous recommendations are found near accurate recommendations. Colors are used to highlight recommendations near accuracy (first three). Using color helps the user identify the potential serendipitous recommendations. Multiple colors are used for alternating recommendations, showing a gradient from accuracy to serendipity. The bubble messages appear when the user's mouse hovers over result table. It conveys system information to the users/stakeholders. This information can be processed related to recommendations. It can also be a computation involved in the client program (JabRef). It is helpful in establishing trust with the user. Social context helps influence the decision-making of the user. The social context provided in the tab is related to the academic environment of the students. The information can be connected via external links that are updated regularly depending on the social context. Seeking serendipity is often associated with interesting surprises in the socio-academic environment.

5 Results

We applied multivariate analysis and linear discriminant analysis for evaluating the significance of various variables such as explanation, serendipity, trust, and user control. The Wilks lambda results show a P value of less than 0.05. It means that there was a significant difference in the user experience. Canonical discriminant function results are given below. Structure matrix and Wilks lambda values are given in Tables 2 and 3. Serendipity, novelty, relevance, difference and language showed significance when multivariate tests were carried out. *P* value for all these attributes was less than 0.05. These statistics show that research students had positive experience when searching for research topic used this software. Although the number of users and total time for usage of the software was not large. It however motivates us to build our user interfaces of discovered design principles.

Tables 2 and 3 showed the significance of the recommender systems attributes relevance, serendipity, difference, novelty and language. The attributes test multivariate analysis indicate that their user interface is significantly different from baseline version user interface. We further calculated discriminant analysis that showed significance as mentioned in Table 4. The test resulted based on Wilki lambda test results. Tables 5 and 6 show the difference in the interface of both interfaces. Attribute wise, it gives us a glimpse of how the user interface can impact the student's research experience while using such system.

Table 4 Wilks' lambda

Test of function(s)	Wilks' lambda	Chi square	df	Sig.
1	0.452	85.771	6	0.000

Table 5 **a** Standardized canonical discriminant function coefficients. **b** Structure matrix

a

	Function
	1
Relevance	0.172
Serendipity	0.716
Difference	0.038
Useful	0.166
Language	0.038
Novelty	0.425

b

	Function
	1
Serendipity	0.843
Novelty	0.571
Language	0.447
Useful	0.394
Relevance	0.363
Difference	0.232

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions. Variables ordered by absolute size of correlation within function

Table 6 Functions at group centroids

Recommender interface	Function 1
0	− 1.082
1	1.101

Unstandardized canonical discriminant functions evaluated at group means

The canonical discriminant for baseline and advance user interface charts reveals that the user experience of the advanced user interface with above mentions visualization and control has a better experience as compared to the baseline user interface of JabRef, as shown in Fig. 6.

Figure 7 shows the clustering of responses by users (students). The responses show that majority of students showed the positively in the favor of the new user interface. This shows that adaptability and acceptance of serendipitous recommender systems in educational setup. We distributed questionnaires to BS software engineering are as follows. The results are shown in Tables 7 and 8. Further Figs. 8 and 9 show that the sentiments of students.

6 Conclusions

Supervising research students through serendipity is a novel idea. Technology enhanced learning domain has still a long road to travel until it offers us useful tools for helping supervisors supervising research students. However, serendipity-based recommender system user interface design gives us enough insights that this approach has potential to new ways of supervising.

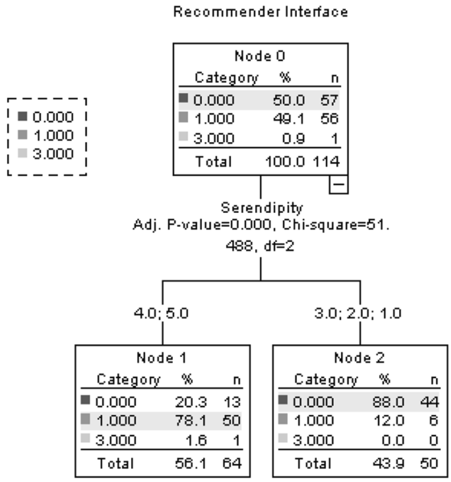

Fig. 7 Clustering of user responses

Table 7 Descriptive statistics

	N	Minimum	Maximum	Mean	Std. deviation
Relevance	114	2	5	4.18	0.719
Serendipity	114	1	5	3.46	1.263
Difference	114	1	5	3.23	0.978
Useful	114	2	5	4.17	0.763
Language	113	2	5	3.95	0.885
Novelty	114	1	5	3.46	1.032
Valid N (listwise)	113				

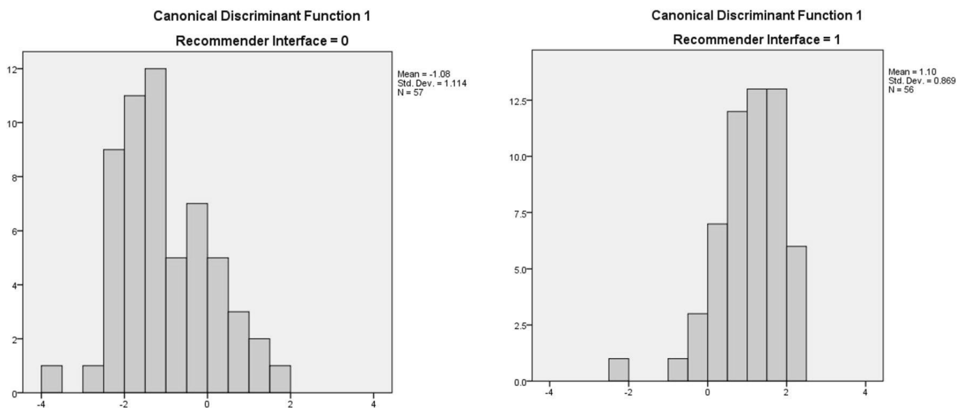

Fig. 6 User experience of advanced user interface for JabRef

Table 8 Descriptive statistics

	N	Minimum	Maximum	Mean	Std. deviation
User control	16	3	5	4.00	0.516
Transparency	16	3	5	4.44	0.727
Support	16	3	5	4.19	0.750
Productivity	16	3	5	3.81	0.834
Attractive layout	16	3	5	4.00	0.816
Explanation	16	2	5	4.00	0.730
Context	16	3	5	4.00	0.816
Novel and interesting	16	2	5	3.75	0.931
Trust	16	3	5	3.94	0.772
Future use	16	3	5	4.44	0.629
Confidence in decision	16	3	5	4.06	0.443
Educational	16	4	5	4.69	0.479
Novel and interesting	16	3	5	4.00	0.730
Will to use in future	16	3	5	4.63	0.619
Valid N (listwise)	16				

Previous theories of user interface design and understanding of recommender systems show us that there is substantial potential in the user interface-based recommender system effectiveness while using in learning activities. The role of context in academic supervision and enhancing learners trust in the overall system is very important to facilitate future uses. Serendipity and recommendation acceptability are still challenging while new user control features, transparency techniques and context awareness of students can help to develop new recommender user interface designs.

(RQ1) Can serendipity be useful in suggesting novel and useful items (research articles) to research students?

Serendipity can be useful in supervision of students. It can facilitate during the topic selection and literature review phase. It's particularly helpful when seeking an innovation or new concept in academia. The bottleneck of coming with new idea with short span of time can be done with a helping hand in innovation and research. The serendipitous recommendation can be applied to other parts of university level education. Primary and secondary level education can benefit from it too but with different datasets.

(RQ2) Does user controlled serendipity facilitating recommender system helps users in research supervision?

In this study users (learners) have shown that they are willing to user such technologies for their research. There are benefits such as novelty, serendipity, relevance and difference of recommendations that can benefit user choice of literature. Further the user also mentioned that their productivity, trust, future use of the serendipitous recommendation can be enhanced using such user interfaces. However, they mentioned that such systems need to accommodate more social context information into the system. That social

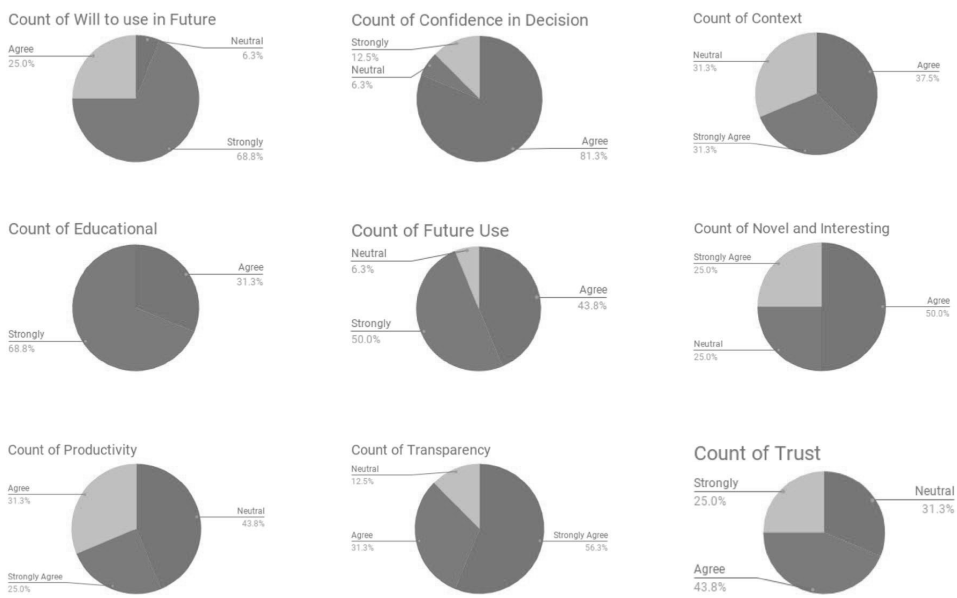

Fig. 8 User responses for academic impact

Fig. 9 Word cloud of users comments

context can be local to the institute/research group, so that learners might know what other students are working on.

One area of future exploration is the usage of context-information-enabled recommender system and transparency related issues when using user-controlled serendipity. The user-controlled serendipitous recommendations need some larger sample sizes and more case studies in order to harness their true potential.

Future prototypes of such user interface require integration of more visualization techniques, user control and transparency enhancing techniques. There is also need for a larger sample size for the survey for better stakeholder's analysis and case testing.

Appendix

Comments from various students (users)

Appreciated work, good design

Quite productive and good quality work

1. It is highly recommended to install this recommender in universities, this will allow students to select a variety of topics for research with ease
2. The recommender should recommend the latest topics for research in which work is already in process

The recommender takes more time to load comparatively. It only shows the research paper while in BS, only research papers should not be recommended. Along with such papers previous projects and related course in order to build that project should be shown

1. Must tell me about the no of individuals who are working/selecting same research topic e.g. which area/field is very popular
2. Suggestions after selecting research topic e.g. scope of it
3. should also show visualization through paragraph about paper popularity or area/field scope for coming areas

1. Show more graph for the better understanding and for showing more details of particular selected topic
2. Create section for comparing topic related to selected topic
3. Create separate section for different other related topics
4. Provide specific and looking good interface for the author name
5. It is very helpful recommender system

1. Helpful
2. System is slow

A very powerful and helpful software if used correctly

It is a very useful and helpful product which can help every student for their educational work. I only have one problem with the product and that is the interface. It should be more visible and easy to understand

System's functionality of recommending some different papers is not necessary i guess

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PUBLICATION IV

Triggers And Connection-Making for Serendipity Via User Interface in Recommender Systems

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ORIGINAL ARTICLE

Triggers and connection-making for serendipity via user interface in recommender systems

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Abstract

This paper reports on the use of transparency in recommender a system that facilitates serendipitous encounters for users. Currently, there are serendipitous recommender systems that facilitate serendipitous encounters; however, there are no studies on the connection-making process or on the process of achieving connection-making through a user interface design. Adding to our previous work on connection-making and serendipity-facilitating recommender systems, we examine transparency in recommender systems as it relates to connection-making we studied transparency of recommendations to foster connection-making. This study is novel as it introduces a new user interface design for recommender system in academia and new study methods and approaches and studies a large group of users who are using this recommender system. The user interface components such as bubble messages on recommender system mechanism, user controls on manipulating the recommender system outcomes and showing authors work addition to recommendation. Repeated measure design of research was used to study serendipity and task load among users for Google Scholar and JabRef related work user interface (User interface developed for Experiment). Subjective evaluation of user interface was done along with NASA-*Task Load Index* for workload measurement. Further sentiment analysis was conducted for validations of findings. Our study finds that serendipitous recommendations and user satisfaction is facilitated via transparency in recommender systems. Furthermore, we found that transparency enhances interactivity for users who are looking for novel and useful recommendations related to their work. This work contributes to human computer interaction studies of recommender systems and reviews the leading literature on transparency, serendipity, and recommender systems in learning environments.

Keywords Serendipity · Transparency · User interface · Recommender system

1 Introduction

1.1 Recommender system development historical view

Since the dawn of recommender systems, there has been an uphill effort for Accuracy of recommendation. While recommender systems introduction in computer systems may be relatively recent, the essential process is neither new nor novel; we are just replicating a social process as described by Resnick and Varian [24]. We receive recommendations from people in various forms, on various topics, and the diversity in recommendations often depends on the person from whom we are receiving them. An ocean of information, regardless of the format, requires a system by which one can select or receive the most relevant information — with or without minimal searching. Ever since they were introduced in World Wide Web, recommender systems have made tremendous gains and occupy prominent places in various domains such as e-commerce, travel, music, academia, automation, and entertainment, to name just a few. As recommender systems developed over time, various new features have emerged with the maturity of each and every component. Next generation recommender systems, as discussed by Adomavicius and Tuzhilin [1], built on the advancements that came to the field of recommender systems. Their research presented a survey of

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recommendation techniques that were collaborative and related to content-based recommendation mechanisms. The survey opened up a new horizon, revealing how recommender algorithms can have best of the both worlds (Content-based and Collaborative-based recommender system) while generating relevant information. However, at the same time, the study reported that accuracy of recommendations needed to be improved in order to generate recommendations in different domains. An article on hybrid recommender systems by Burke [9] describes the technique of pushing for peak performance by combining the capabilities of recommender systems. The recommender systems described basically focused on and mostly relied on algorithmic-based recommender systems. As recommender systems started to make their way into various domains, the learning technologies became one of the pioneering fields which lay the breeding ground for recommender system development. Drachsler, Verbert, Santos, and Manouselis[10] describe recommender systems for learning and their use in the field of education. The majority of their research focuses on the reflection-oriented technology, in which recommender systems play a central role in what is called 'recommender system for technology-enhanced learning'. The contextual information was identified as one of the major needs of this future technology. As work continued to progress, Verbert et al.[33] presented a study on context-aware recommender systems in learning. This giant leap involved context-aware computing for recommender systems, specifically in the field of education. The dynamic profile of a learner was key to harness the element of context for recommendation modeling and to create better results for learners.

After much research and development, recommender systems that provide learners with relevant references to resources, such as books, scholarly articles, lectures, and many more, have been successfully implemented. The impact of recommender systems has been widely acknowledged and, hence, many educational institutions and research groups support the use of recommender systems in teaching and learning. Educational recommender systems are also widely used and installed in digital libraries due to their ability to recommend relevant items in a vast sea of data. Most commercial and open-use systems such as Google Scholar or other reference management software have built-in recommender systems. The built-in system calculates the relevance of recommendations from the educational dataset, such as scholarly articles, and from user behaviors, such as the number of citations or downloads and author/user profiles. Almost all of these recommender systems have a simple user interface that works on the basis of the accuracy of its recommendations.

Serendipity in these systems, however, has not been widely attempted via user interface. Instead, various studies have been conducted to analyze the accuracy of recommender systems. Nevertheless, there is a present need for serendipity facilitating recommenders in learning and in the field of education. Additionally, there is a need for more research on serendipity-oriented recommender systems as they must be fully understood before they are applied in academia.

Unlike the conventional recommender systems, the serendipity-oriented recommender systems are not common. The concept of the serendipity itself is relatively unstudied, in general, and is certainly new in terms of the application of the recommender systems. Rather than aim to achieve accurate results, the serendipity-facilitating recommender systems intend to facilitate surprising new perspectives related to a problem or topic. Academic and research innovation is one such area where novelty and diversity, combined with usefulness, is always welcome. Therefore, due to the subjectivity inherent in the output of a recommender system, studying serendipity in a recommender system will require in-depth, long-term study. Only a large number of case studies can do that.

For this research, we selected JabRef, an open-source reference management software. It has a related work tab, which recommends research articles related to the paper selected by the user. The recommendations are generated by another open-source recommender, also called recommender-as-a-service Mr. Dlib. Mr. Dlib are integrated into JabRef for recommender[12]. Mr. Dlib[8] is a recommender-as-a-service. It suggests relevant papers and academic articles based on user searches using JabRef. Mr. DLib uses a context-based recommendation engine. It is open-source and open for novel recommendation algorithm implementation. The recommender is accuracy-oriented and returns a few recommendations results.

Serendipitous recommender systems are mostly algorithmic with slight variances in user interface. The interactive element of recommender system is accuracy-oriented. The serendipity feature is not connected with serendipity-oriented algorithms nor does it work independently with accuracy-oriented algorithms to achieve serendipity. At this time, the vast advances in context-aware computing and data visualizations have not yet been exploited for generating serendipity in recommendations. Therefore in this research we attempted to facilitate serendipity of recommendations via recommender system user interface. Connection-making was focus of visualizations and controls used in user interface of recommender system. Our study provides an alternative to algorithm based serendipity facilitation in recommender system.

1.2 Past research on serendipitous recommender Systems in Academic Research

Studies have been done previously on interactive recommender systems, facilitating serendipity in learning environments. Initially our work started with using user controls for the facilitation of serendipitous recommendations. Since it is a relatively new phenomenon, the work was mostly focused on educating students and teachers on the topic of serendipity

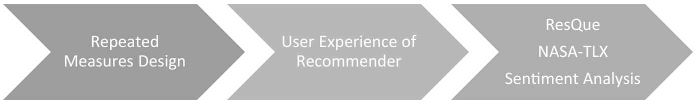


Fig. 1 Research design

and its application in digital technologies, such as recommender system[3]. We conducted stakeholder analyzes which revealed that there is, indeed, a desire among learners and faculty for serendipitous encounters; however, there is little knowledge about the topic [2]. We investigated user choices for visualizing recommendations that have the potential to facilitate serendipity[4].A few visualization techniques emerged, but conclusions were limited since most of the studies were conducted with a user sample size of 20 to 60 participants, and another study with 100 users[6]. We learned that an interactive recommender system that facilitate serendipity has great potential in academic research, and may also influence recommender system designs in other domain such as e-commerce, elder care, tourism, and project management. Continuing our work, we conducted studies on instructors' needs for serendipity and the recommender systems that are capable of facilitating this process[5]. We analyzed industrial, state-of-the-art recommenders for their potential to generate serendipitous encounters and considered how a serendipitous recommender system might further fulfill needs in academia. Our investigation on facilitating serendipity in academic research in a university environment generated some positive results, as discussed by Afridi et al. [7]. While all of these contributions were in the field of human-recommender interaction, the study revealed larger discoveries on the nature of serendipity and need for advance recommender systems in academia.

Previously, we learned that serendipity-oriented recommender systems are not being used in academic research. We also discovered that there is great potential to redesign and customize user interfaces of such recommender systems in order to facilitate serendipitous encounters. As far as academic environments are concerned, both the concept and application of serendipitous recommender systems are still in their infancy. The initial studies are, however, showing a positive outlook as well as an indication of success for such systems. The industrial application of interactive, serendipitous applications in academia is still distant due to many reasons. Our research forms the baby steps that will lead scientists and engineers to move in the direction of developing such applications. The biggest contribution to this endeavor may be to conduct studies that include a larger and more diverse sample size. Furthermore, there is need for additional qualitative and quantitative research techniques, as well as more user-centered and data-centered evaluations of recommender system. Together, these techniques and evaluation scan help us to take these prototypes from the lab and on to industrial applications. At present, we are focusing on connection-making

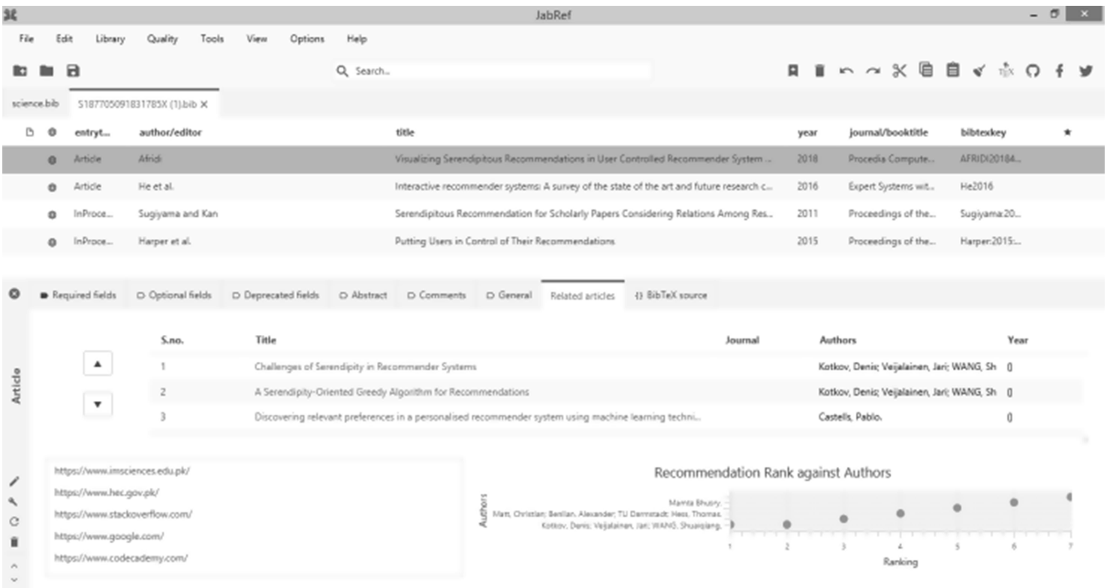


Fig. 2 User interface of JabRef in evolving for serendipity

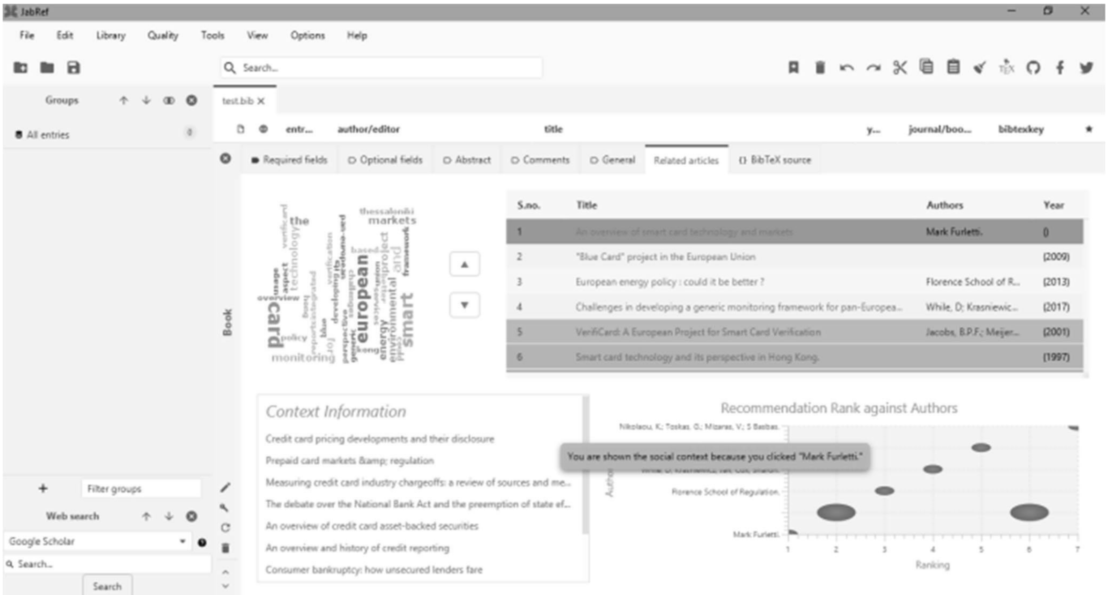


Fig. 3 User interface of JabRef in related work [6]

and contextual information usage in our continuing prototype development. There is, however, a need to incorporate both an algorithmic approach as well as a non-algorithmic approach into serendipity-oriented applications.

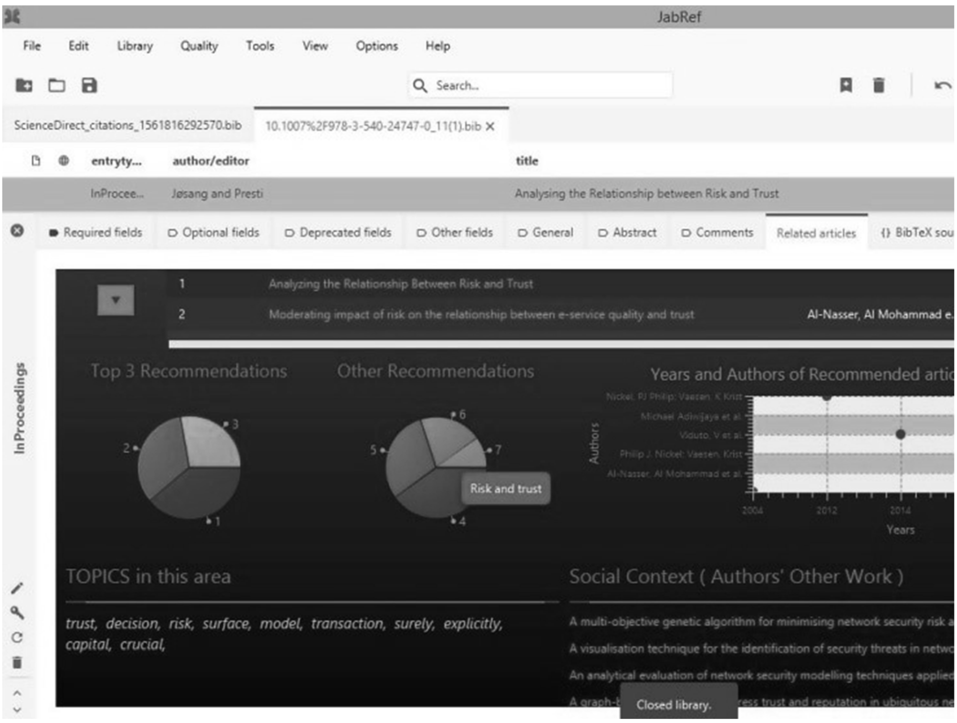


Fig. 4 User interface of JabRef-related work tab

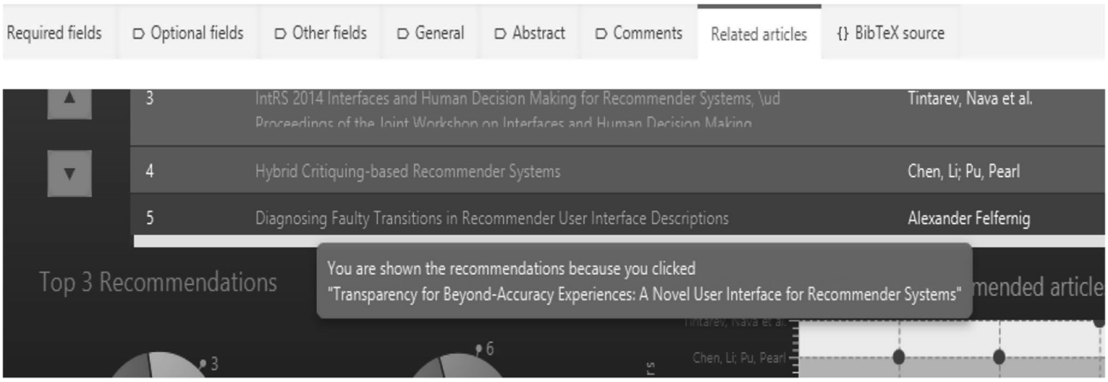


Fig. 5 Explanation of recommendations on mouse-over

1.3 Challenges to researching serendipitous recommenders in academia

There are challenges associated with researching and discovering the true potential of user interfaces for achieving serendipitous encounters through technology. First, there is the existing, dominant classroom model in which learning takes place in a structured manner, according to a fixed course outline or predetermined route. Second, the way in which learning is driven by faculty—which is good, in a way, as it offers the opportunity for instructors to provide guidance—can discourage a student to work based on recommendations/problems suggested by software. These recommendations may seem to be too new and have an inherent uncertainty with respect to outcomes since they are associated with serendipity. Furthermore, as there are no exemplary serendipitous technologies, even outside of the recommender system domain, we conclude that the pioneering work related to these experiments must be preceded and followed by rigorous education of academic and research environments, in general .

1.4 Need for additional research

Existing recommender systems deployed and used in the academic environment, and even the nonacademic environment, are accuracy-oriented; however, it is possible, through studying and developing interactive recommender systems, to facilitate serendipitous outcomes. Furthermore, even serendipity-oriented algorithms have even not made out of labs; therefore, user-interface-driven serendipity studies in addition to accuracy-oriented recommender system is a suitable approach for experimentation and changing users' perception and experiences.

1.5 Contributions made by this research

This paper makes several contributions. First, it provides a real case study for academic institutions to utilize a serendipitous recommender system with an advanced user interface developed specifically for serendipity facilitation. Second, it offers the opportunity for enhanced understanding of human-recommender interaction. Third, it shows how transparency at the user interface level for recommendations has potential. Fourth, this paper introduces a novel user interface. Last, but not the least, we also introduce and discuss what kinds of serendipitous encounters have been introduced by using such technologies. This paper is composed of six sections. Section 2 describes the current literature on this topic. Section 3 describes our experiment design, while Section 4 describes the experiment. Section 5 summarizes and discusses the work. Last, Section 6 offers directions for future research directions.

2 Related work

Transparency and serendipity are both related at a certain stage in recommender system user interface design. Connection-

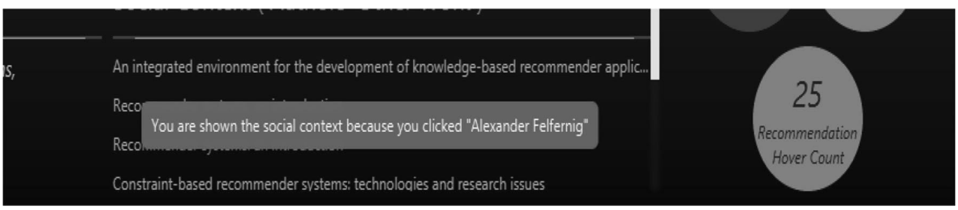


Fig. 6 Explanation of social context on mouse-over

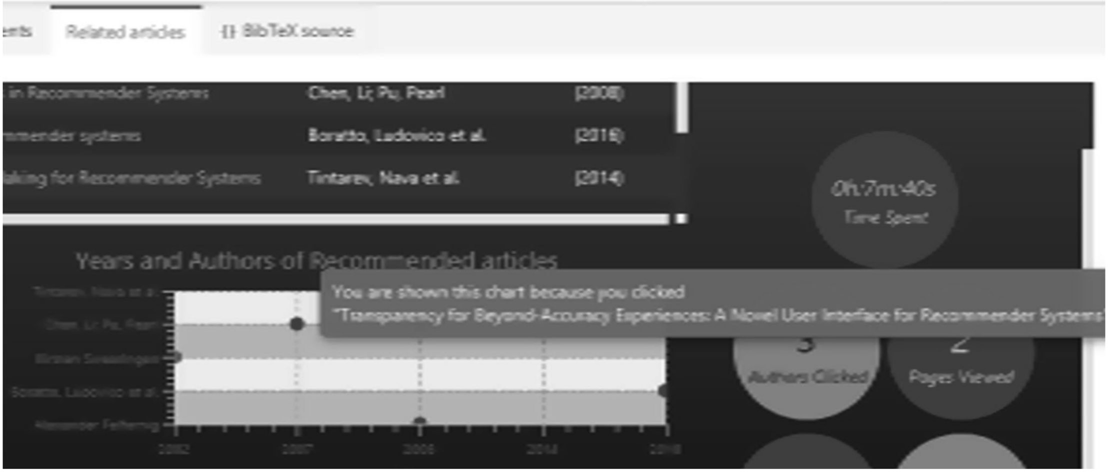


Fig. 7 Explanation of years and authors chart of recommended articles

making is difficult, but successful connection-making can result in serendipitous experiences. While connection-making can be facilitated, there is still a large void in the literature. In our study, we questioned: What kind of user interface design and narrative can help foster connection-making? Is user interface as successful as it seemed in a previous case study by Afridi et al. [7]? Transparency has indeed facilitated connection-making that resulted in serendipitous experiences, as studied earlier in limited scale by Afridi [6];however, more evidence and explicit studies with larger sample sizes and insights are needed to form and test new prototypes to establishing this observation. Work by Sugiyama and Kan [27] and work by Thudt, Hinrichs, and Carpendale[28] called Bohemian Bookshelf are important to this research. Sugiyama and Kan proposed a model for connection-making, targeting scholarly work through algorithmic serendipity. Work by Thudt, Hindrichs, and Carpendale focuses on graphically presenting digital library content and scholarly works. Both of these works contain form a foundation on which we have built and advanced our own work

Kotkov, Wang, and Veijalainen [20] performed a survey of serendipity across various domains. Their survey elaborates various aspects, taxonomy, and classifications of serendipity. It also briefly discusses how to achieve serendipity in a digital environment. The authors argue that the prepared mind, along with a trigger, can achieve serendipitous experiences. The 'triggers' are explained as an "inspiration for a novel result" ("act of drawing initial attention"). The authors refer to the bridge as the "why" phase of serendipity. In this paper, we attempted to use contextual information as an attention-drawing mechanism that can be used as a trigger, and user explanations of recommenders as "why" phase. Kotkov, Veijalainen, and Wang [19]discuss various aspects related to the challenges of facilitating serendipitous experiences, including the emotional dimension. We are also motivated in our research to consider the mental demands and other related difficulties through task load index developed by NASA.

He, Parra, and Verbert [15]study interactive recommender systems. The study covers the interactive, user interface aspects of recommender system, in detail, presenting a dissection of the layers and components of successful interface

Fig. 8 Article title and details for other related work upon mouse-over

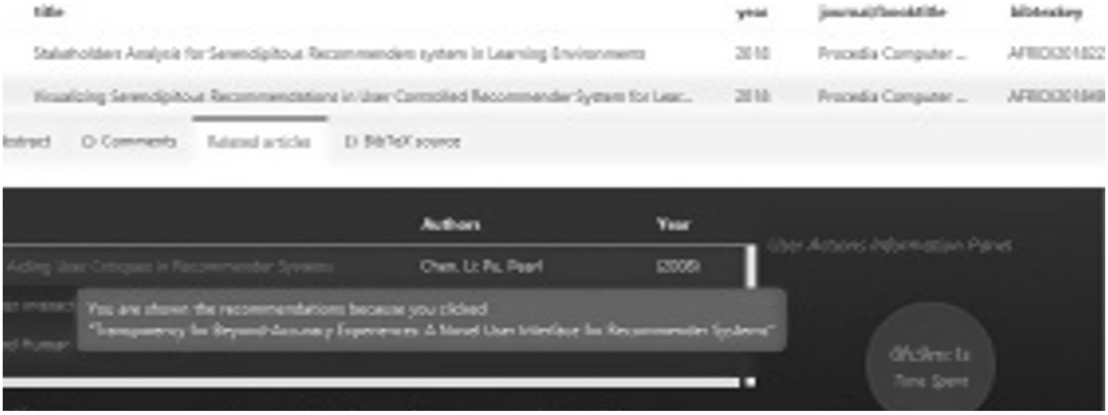


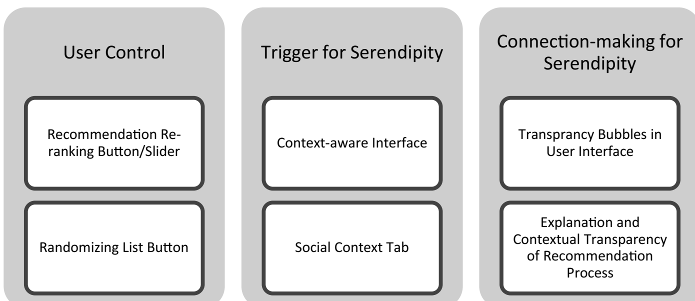
Fig. 9 Explanation of related work table

design developed for recommender systems. Serendipity and user feedback are important, as described in the research by Kotkov, Konstan, Zhao, and Veijalainen [21]. In their study on serendipity, the authors included 475 users as a sample group. In their paper, the authors argue that there are three components of serendipity: relevance, novelty, and unexpectedness, with multiple variations. Their findings show that unexpectedness has a negative effect on user experience.

Research by Tsai and Brusilovsky [32] reports on control, visualization, and interactivity with regard to diversity in recommenders. Their paper presents the idea of diversity enhancement via user interface in recommender systems. A new user interface was developed and evaluated for the study. The researchers report that the user interface can reduce exploration effort. Tsai [30] also studied and discusses diversity in recommendations and recommender systems user interface, concluding that the recommender system user interface constitutes user experience and social interaction. User interfaces, through visualizations, can enhance the diversity of recommendations. This diversity can increase user satisfaction. Here, is important to note that user interface can be instrumental when designing diversity-oriented recommender systems. Verbert, Brusilovsky, Wongchokprasitti, Parra, and Cardoso [35] discuss supporting conference proceedings with decision-making through rich graphical user interface of recommender systems. Their work shows the importance of human factors. The prototype was implemented through relevance information /feedback by user and bookmarking/tagging. It is likely the case that the idea may be useful for achieving serendipity as well.

Transparency of recommenders has also been researched over time. Verbert, Parra, Brusilovsky, and Duval [34]studied transparency and visualization though an interactive recommender system. Their study presents talk explorer, a recommender based on interactivity and transparency. Kefalidou and Sharples [17]describe connection-making and transparency by unpacking the process of transparency. He, Parra, and Verbert [16] argue that, beyond accuracy studies, there are additional goals for recommenders to be effective in terms of user satisfaction, including trust, transparency, and user control. The authors present a framework for recommender system HCI (human-computer interaction). The role of transparency of recommender system has also been studied by Sinha and Swearingen [26]. Their paper presents five music recommenders to study human-computer interaction issues, revealing how transparency can lead to user confidence in the system. Explanations in recommender systems play an important role, as described by Tintarev and Masthoff [29].

Fig. 10 User interface design factors with implemented features



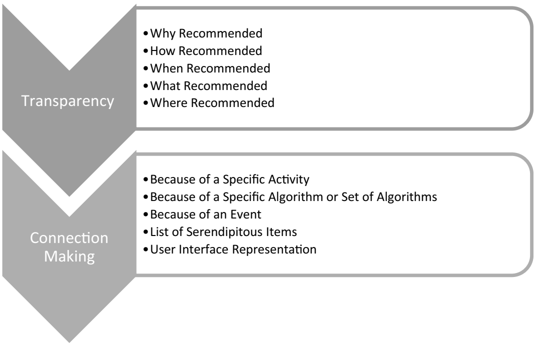


Fig. 11 Converting transparency to connection-making element in user interface

Their paper shows how personalization decreases effectiveness over time. In their study, each explanation has seven aims: effectiveness, satisfaction, transparency, scrutability, trust, persuasiveness, and efficiency. Their paper is a step toward user-centric evaluation and represents an increase in such kinds of recommender system evaluations.

Explaining recommendations using context has been studied by Sato et al. [25]. A context-style explanations method approach can be both persuasive and useful. Additional context helps users make the right choice. Goodman and Flaxman [13]have discussed the right to explanation. They discuss the opportunity to develop algorithms, design evaluations that avoid discrimination, and create frameworks that enable explanations. Kizilcec [18]has discussed algorithms and justification issues. The author argues that providing too much information erodes trust. The author also argues that when expectations were not met, greater transparency did not have much impact. When designing user interface to increase trust, it was important that software balanced interface with transparency. Evaluation recommender explanation by Tintarev and Masthoff [29] showed that user were satisfied with feature-based explanations. In our own work, we aim to provide user interface and control-based transparency for connection-making.

3 Research design

This research article is aimed at investigating key research questions regarding serendipitous recommender system connection-making mechanisms. The study design follows that of Tsai and Brusilovsky [31] and the user-centered study design by Fazeli et al. [11].The research questions are as follows:

1. **RQ1** Can user interface facilitate connection-making that contributes to Serendipity of Recommendations?
2. **RQ2** Can user interface facilitate trigger of an idea that contributes to Serendipity of Recommendations?
3. **RQ3** Does recommendation re-rank via user control along with transparency of recommendation mechanism facilitate serendipity?
4. **RQ4** How does user-interface-driven serendipity impact the user's cognitive load?

The key steps of our investigation are as follows:

1. **Recommender system user interface development.** This stage involved the development of a new user interface for the related article tab of JabRef reference management software.
2. **User-centered evaluation.** A questionnaire-based study collected data from users and allowed for a user-centered analysis of the user interface.
3. **Record user interface task load**. User activity while using the recommender was recorded and analyzed.

This research has been conducted using a **repeated measures design**. The main rationale for using a repeated measure design is that serendipity is a rare phenomena and it is ideal to detect it with a repeated study. Second, we used an experimental setup in a lab environment for studying the user experience with the recommender user interface (Figs. 1, 2 and 3).

Our investigation is different from previous investigations (as shown in Figs. 2 and 3) of serendipity. First, this study uses/proposes new statistical tests. Second, the new user interface that has been developed will not only validate or reject our previous findings; it will also help us understand and investigate new findings. Third, this research will help us to create a model of user interface design that facilitates serendipity. Fourth, this study helps us to test the user cognitive load using NASA-TLX scale[14, 23]. User interfaces from previous studies we conducted is shown in the following figures.

The recommender system developed for this study, along with specific sections of the user interface, is shown in Fig. 4. The new user interface specifically follows serendipity-model-inspired design guidelines. The model has been presented by McCay-Peet, Toms, and Kelloway [22]. The user

Table 1 Wilks' Lambda

Test of function(s)	Wilks' lambda	Chi-square	df	Sig.
1	0.487	46.426	11	0.000

Table 2 Wilks' lambda

Test of function(s)	Wilks' lambda	Chi-square	df	Sig.
1	0.486	50.885	11	0.000

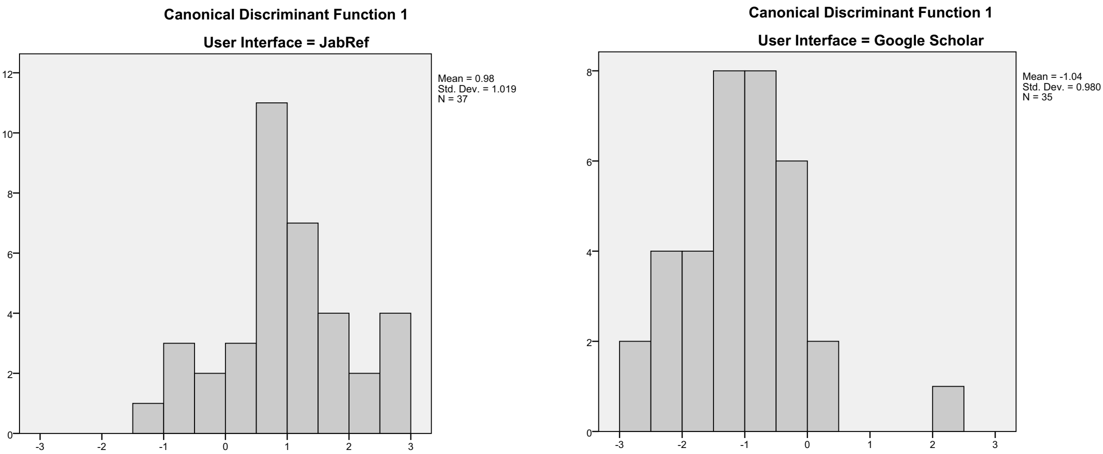


Fig. 12 Charts for discriminant function

interface presents users with recommendations that are facilitated by multiple user controls; by transparency of the recommendation presented; and by social context with respect to the research under consideration. The user interface also calculates the user interface activity for tracking activity.

Figure 4 shows a complete picture of new user interface developed for serendipity. The interface consists of user control options for facilitating serendipity, contextual information, and transparency of recommendations. All of these features are used to create a combined effect that is intended to better facilitate serendipity. Detailed shots of the user interface are as shown in Fig. 5.

When the user hovers over the table of recommendations, a bubble message appears that explains to the user why the item has been recommended as shown in Fig. 5. Similarly the mouse over the authors other work shows as social context message as shown in Fig. 6.

When hovering over the results for authors' other work, a message bubble appears explaining that the recommended works are from the same author who was selected as part of the original query. Authors' work and years of publication are provided to update users on timeline of the years the topic related work as shown in Fig. 6.

The table that appears upon mouse-over explains why these authors and years are present on the scatter plot chart and indicates the year in which recommended articles were published and from which author. The serendipitous output and transparency bubble are shown in Fig. 7.

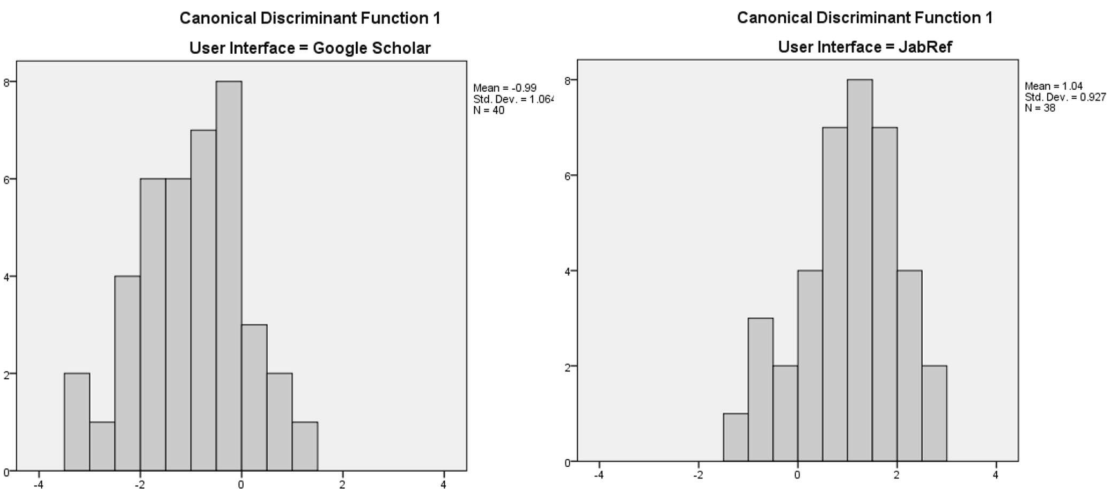


Fig. 13 Charts for discriminant function

NASA TLX Results for Google Scholar and JabRef for Both Data Collected

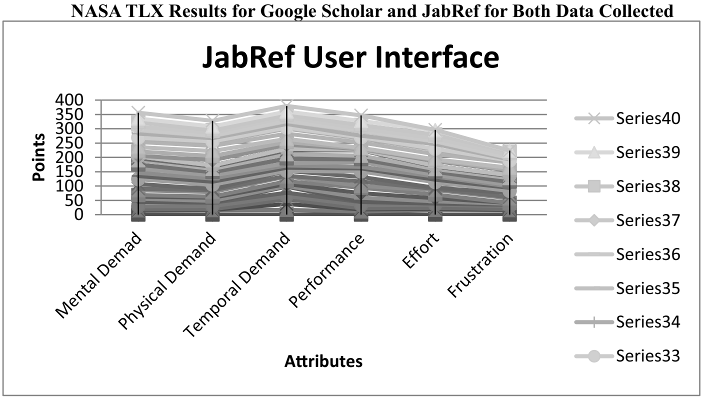


Fig. 14 JabRef related work NASA-TLX data

The potentially serendipitous recommendations are represented in the pie chart (Fig. 8). Each representation is linked to results in the recommendations table, which is revealed upon mouse-over.

Our arguments for connection-making from transparency is explained in Fig. 9. Transparency can lead users to think and reflect upon some aspects of recommendations, leading them to connect one concept or idea to another (Fig. 10). The diagram (Fig. 11) shows how users can transition connection-making after being presented with transparent information. Any significance in transparency and serendipity can lead us to conclusion that connection-making has made a role in facilitating serendipity. The bubble on the recommendation table in (Fig. 9) shows why some specific papers were recommended. Furthermore, the user interface also shows user activity statistics for the JabRef recommender's user interface (Table 3). The study revolves around components of serendipity, as described by McCay-Peet [22]. The interface for recommender system revolves around the design of enhancing user control, contextual information usage, and transparency for connection-making. All three areas that are interrelated in this study are shown the diagram below (Fig. 10).

4 Experiment

The experiment involved B.S. Computer Science students and M.S. Computer Science students at the Institute of Management Sciences, Peshawar as they selected a topic for their final year project theses. The students provided the JabRef with an initial, base paper so that the related work tab could recommend a few papers. The data collected was for a total of 40 users (students). The students, and the presenter of the software on multimedia display, used the software for approximately 45–60 min for one session. The students were presented with various features and usage scenarios of recommenders, along with usage and analysis of user interface of Google Scholar. Google Scholar was used a baseline since it is mostly used and is a standard tool in academia. We applied Multivariate test as mentioned and discriminate analysis on data collected on the scale of ResQue Model for recommender sysetm subjective evaluation. Since it was a repeated measure design study, data was collected twice for both Google Scholar and JabRef. Discriminant analysis was conducted in order to measure significant change in the attitude of students (users) toward both of the recommender

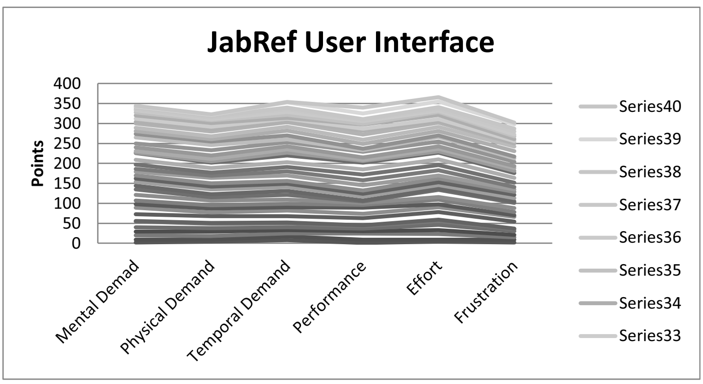
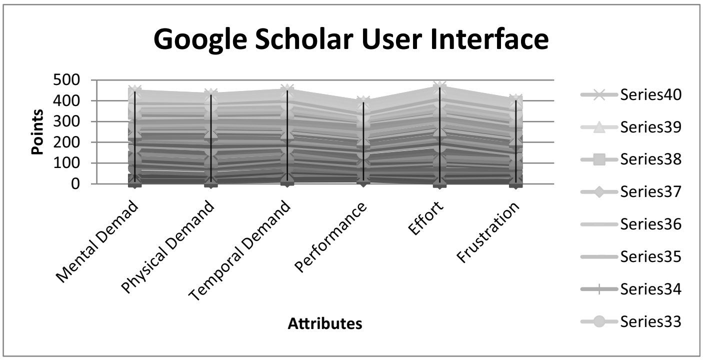


Fig. 15 JabRef related work NASA-TLX data (Repeated)

Fig. 16 Google Scholar user interface NASA-TLX data



system. Multivariate test results showed significance of Pillai's Trace. Further Hotelling's Trace and Roy's largest Root show significance.

The significance of these test show significance of effect. It's also robust as compared to the other tests as mentioned. Tables 1 and 2 shows Wilks lambda for JabRef and Google Scholar interface. It shows significant difference between these two user interfaces. The since studies were conducted twice, so the results of first study and second are presented below (Tables 1 and 2).

4.1 First study results

4.2 Second study results

The Analysis shows significance for all the variables except Context and difference in both times for JabRef and Google Scholar User Interface (Figs. 12 and 13). Usefulness and Surprise significance difference along with significance of Transparency and interface adequacy shown in Figs. 14 and 15. The JabRef user interface role in facilitating serendipitous experience for users. The significance values are shown in Table 1. Table 2 shows the significance of Wilks lambda for both recommenders user interface. The charts in Figs. 16 and 17 shows that there is positive trend for JabRef shown in user interface. The data collected on the scale of NASA-TLX was collected. The comparative results of both of the user interfaces show that JabRef has lower effort requirements and frustration to users. Google Scholar on the other had has higher effort requirement and frustration values. The results are shown in Figs. 14, 15, 16, and 17.

5 Sentiment analysis of developed prototype

We performed the sentiment Analysis of our prototype with Intencheck, free sentiment Analysis software available online. The results of the analysis are given below in Tables 3, 4, 5, and 6.

Results from Text Mining (Sentiment Analysis of Comments Section) for Google Scholar

6 Discussion

Previously, in studies Afridi [2, 5] we believed that user interfaces that facilitate serendipity must have the components of idea trigger and connection-making for those ideas. In the results mentioned above, we can conclude that users do, to a large extent, encourage facilitation via user interfaces. We

Fig. 17 JabRef related work NASA-TLX data (Repeated)

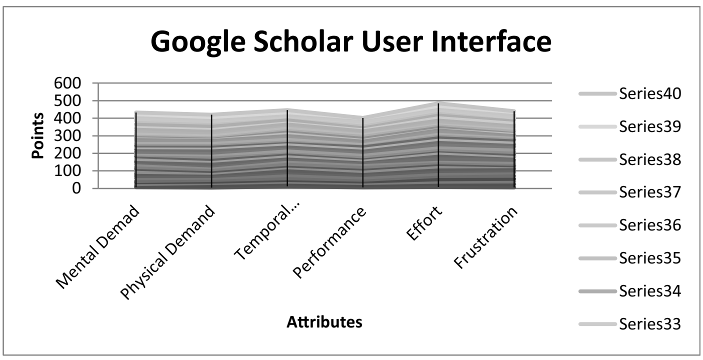
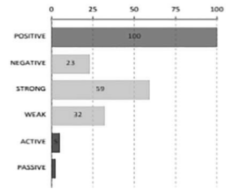


Table 3 Sentiment Analysis of JabRef

RESULTS

ATTITUDE GROUP

Category	Grade	Value	Words	Highlighted words
POSITIVE	VERY HIGH	100	18	beautifully, better, clearly, easy, efficient, friendly, good, helpful, impressive, informative...
NEGATIVE	NORM	23	7	dark, dull, hard, least, little, need, problem
STRONG	NORM	59	10	add, efficient, impressive, more, much, possible, productive, recommendation, search, wide
WEAK	NORM	32	3	dull, little, need
ACTIVE	VERY LOW	5	12	better, conclusion, explanation, explore, get, make, put, research, search, show, use, work
PASSIVE	VERY LOW	2	8	dull, hard, like, need, related, see, single, support



verified the reliability of our previous studies that indicate that serendipity can be facilitated via a user interface through novel user interface design. The design was based on the principles of connection-making and trigger via user interface components. The validity of previous work also encourages us to further develop more prototypes and test the validity of our concepts. The experiment has increased the usage of our prototype and, therefore, has produced more data. The roots of our inquiry, however, still remain in the user-control-based serendipitous recommendations. The notion of user-interface-driven outcomes and serendipitous encounters are welcomed by students and gives us enough reason to test it further in other fields. The NASA-TLX-based questions for Google Scholar related work interface and JabRef-based related work user interface helped us to understand user perceptions and cognitive load while using both interfaces during the research. JabRef had a good cognitive load and impact on users while Google Scholar's user interface was considered to have a greater cognitive load. Our study revealed that there was a significant difference in the task load index of the two interfaces. Contextual information, in the form of social context, is still believed to be a major factor in triggering ideas for the user but results did not prove this statement. The impact of contextual information on serendipitous encounters need to be studied in both objective and subjective ways.

We therefore presents answers to our research questions.

1. **RQ1** Can user interface facilitate connection-making that contributes to Serendipity of Recommendations?
2. **RQ2** Can user interface facilitate trigger of an idea that contributes to Serendipity of Recommendations?
3. **RQ3** Does recommendation re-rank via user control along with transparency of recommendation mechanism facilitate serendipity?
4. **RQ4** How does user-interface-driven serendipity impact the user's cognitive load?

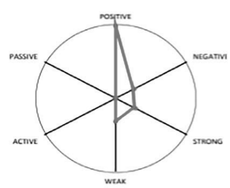
Connection-making can be facilitated via user interfaces for achieving serendipity in recommender systems. The explanation of various recommender system features at the user

Table 4 Sentiment Analysis of JabRef (Repeated)

RESULTS

ATTITUDE GROUP

Category	Grade	Value	Words	Highlighted words
POSITIVE	VERY HIGH	100	21	above, attractive, better, catchy, clean, convenient, ease, easy, even, friendly, good, help, h...
NEGATIVE	NORM	26	6	close, dark, less, low, problems, stress
STRONG	NORM	28	14	accomplish, additional, big, effect, every, high, lot, main, more, much, physical, project, rec...
WEAK	NORM	32	5	fall, help, light, relax, small
ACTIVE	VERY LOW	0	11	accomplish, better, clean, combination, do, effect, stress, take, task, use, work
PASSIVE	VERY LOW	0	7	fall, like, love, project, related, relax, want



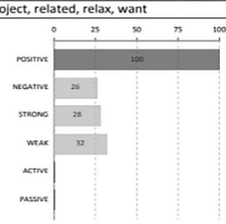


Table 5 Sentiment Analysis of Google Scholar

RESULTS

ATTITUDE GROUP

Category	Grade	Value	Words	Highlighted words
POSITIVE	VERY HIGH	100	20	above, attractive, better, content, dynamic, ease, easy, even, friendly, good, impressive, just...
NEGATIVE	NORM	49	13	boring, complex, confusing, difficult, discouraging, hard, lack, less, little, need, stressful,...
STRONG	VERY LOW	4	9	dynamic, found, full, impressive, lot, much, recommendation, search, sufficient
WEAK	LOW	9	4	lack, little, need, only
ACTIVE	VERY LOW	0	10	better, dynamic, found, get, introduce, representation, research, search, show, use
PASSIVE	VERY LOW	5	13	been, boring, content, hard, identify, known, lack, need, normal, quiet, reduced, related, usel...

interface level helps user connect various ideas. Serendipity may or may be not experienced by users but it is significance in the results as it has a positive impact on the user interface design approach.

Triggers can, indeed, be made via user interfaces for serendipitous recommender systems. This question was tested by facilitating authors' other work information support, labeled as social context. It did not show any significant difference form Google scholar; therefore, it cannot be conclusively declared that contextual information might had a trigger role for serendipity in this study. User interface activity may have an impact on the user's experience of serendipity. The significance of surprising and useful recommendations indicates that serendipity can impacted by a user interface design of recommender system; however, the interface must provide all necessary elements of serendipity. There is a cognitive load placed on users when they are experiencing serendipity via a user interface. The user interface that facilitates serendipitous encounters does have a greater cognitive load as compared to JabRef as baseline study. This finding suggests that too complex user interfaces might lead to confusion and disarray as users interact with serendipity-oriented recommenders.

7 Conclusion and future research directions

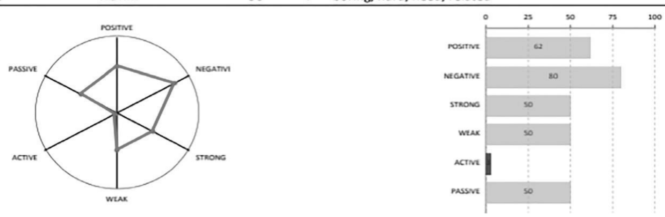
This research aimed to investigate the role of the user interface design in serendipitous recommender systems used by students. The study was carried out by repeatedly testing two recommender system user interfaces among a group of users. The two recommender systems included in the study were Google Scholar and JabRef—Both of which are research article recommenders. The experiment included participants among B.S. and M.S. students at the Institute of Management Sciences, Peshawar. Students evaluated both recommender user interfaces by using them as they sought to select potential topics for their theses. The user controls were developed for facilitating serendipitous encounters. The

Table 6 Sentiment Analysis of Google Scholar (Repeated)

RESULTS

ATTITUDE GROUP

Category	Grade	Value	Words	Highlighted words
POSITIVE	NORM	62	4	friendly, good, recommended, simple
NEGATIVE	NORM	80	4	boring, hard, hectic, need
STRONG	NORM	50	2	much, provide
WEAK	NORM	50	2	need, only
ACTIVE	VERY LOW	3	2	effort, select
PASSIVE	NORM	50	4	boring, hard, need, related



user interface included bubble messages to provide transparency of functions. List with user controls for reorder button controls were used to display recommendations and pie charts were utilized for accuracy and near-accurate recommendations.

The experiments suggest that serendipity is a valuable experience in the learning environment, in particular, and has great potentially in most information-centric industries as well. The user interface developed for this study create a user perception of serendipity, as facilitated by the interface. User controls played an important role in manipulating and creating a serendipitous encounter,as there was a significance in the preferences expression and altering outcomes of the user interface. The repeated measurement showed the same impact over time. Successful serendipity requires connection-making and triggers, along with all other elements. The user interface attempted to facilitate connection-making, and user data shows that significance of transparency of recommendations and the system, as well as its role in helping users to understand the recommendations. Furthermore, the data shows the significance of interface sufficiency for serendipity and relevancy of recommendation. JabRef shows less user effort and frustration as compared to Google Scholar, based on the task load scale. Furthermore, the data shows that JabRef can facilitate serendipitous user experiences to a greater extent, as compared to Google Scholar. Serendipity as a recommender sysetm dimension is interesting but generally important for the information system based academic and research environment too. This research enables us to foresee a future were students, teachers, and researcher not only fully understand the phenomenon of serendipity but also can harness it. The results of this research are promising and provides us base for developing further prototypes for serendipitous data sets based recommender systems

One potential future study might be a detailed subjective analysis of the contextual information and serendipity facilitation. Furthermore, the rise of internet-of-things-based applications can further strengthen the importance and applications of serendipity-driven recommender systems. User control, on the other hand, is influencing the serendipity experience of the learner. Future research should investigate the negative outcomes and the boundaries of serendipity, along with the limitations of recommender systems to facilitate serendipity. The limitation of users experiencing serendipity in their interaction with recommender systems is still far too small to generalize. Regardless of their focus, these future studies must be replicated and expanded to broaden our understanding of user experiences of serendipity and recommender systems in teaching and learning

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ANNEXTURE

Users Comments for the User Interface Improvements for JabRef-related Work Tab Developed for This Experiment.

- User interface is very helpful and informative for researchers and schools, but I suggest toadd an option at year wise recommendation. User interface data was highly helpful
- User interface is good but should be more clear,self-explanatory
- The user interface is simple and graphic support product is efficient
- Simple UI, need color change and click count, and paper clicked portion can be at the bottom of UI. The data suggested were seems useful to use
- It’s good. UI is good, search should be more wide
- Filter feature, future work not showing
- He has put some pages work on a single platform it’s more helpful for research field. Beautifully arranged, very impressive
- The UI is overall good, if there is a filter by year by research field that would be more user-friendly
- It is a productive software
- Color theme is a bit dull, otherwise it’s good. Interface is a bit scattered
- The interface is better and easy to use. I think you need to add at least 10 papers at a time to see in reviews, which is related to key
- The graph is easy to understand, shows more detail about the research. Interfaces are good, show research paper recommendations
- To the point, interesting graphs, easy to use, colors are little dull. 7 m time taken, 1 page viewed
- All type of graphical things can be displayed on it, easier to get related documents. Make a graph to explore the author profile which is based on citation
- Filter must be included,conclusion of articles, too dark, it must be brighter so it should be clearly visible
- User-friendly. Is easy should also have conclusion. Charts in bar are friendly
- Interface is good but need some color changes and titles for charts
- Color themes used are hard which creates visibility problems. It’s possible the contents should be covered in available screen site rather than scrolling
- Search field is required
- Good, but if the search paper will categorize into 3 to 4 stages like abstract, introduction, explanation or working and conclusion individually

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PUBLICATION V

NASA-TLX–based Workload Assessment for Academic Resource Recommender System.

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ORIGINAL ARTICLE

NASA-TLX–based workload assessment for academic resource recommender system

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Abstract
Recommender systems are expected to promote a student-centered teaching and learning environment. The age of information abundance has proven to need such systems. Recommender systems have been used to recommend learning items related to students' research interests. Serendipity has also made its way into the academic environment, as systems recommend items that are useful and surprising to learners. Understanding user workload is important for students who use serendipitous recommender systems. In this research, we investigate various user interfaces for academic recommender systems by looking at students who are attempting to obtain serendipitous recommendations for their academic tasks. The study was evaluated on the NASA task load index (NASA-TLX). Our priority was to understand the mental, physical, and other workload attributes that can change when students seek serendipitous recommendations. We studied Mendeley, Google Scholar, Academia.edu, and ResearchGate. Our study found no substantial serendipitous recommendations observed by the users, but a few traces of serendipitous experiences were observed. Further, no substantial workload was detected in using the systems. However, the recommender system did create different user experiences across repeated sessions. Further, a diverse range of task loads is associated with the recommenders used in academia, from mixed designs with rich user controls to very few controls. This research provided us with insights that can be used to help designers incorporate and accommodate new features and take calculated risks when designing serendipitous education technology.

Keywords Serendipity · Transparency · User interface · Recommender system · NASA-TLX

1 Introduction

As with any technology, there must be some potential downsides to interactive recommender systems that, with the help of user interfaces, facilitate serendipity. Likewise, there must be some costs associated with the application of serendipity or user control to a recommender system output when research interests or workloads change. When a user is interested in serendipitous recommendations and uses an interface to obtain them, there must be some goal. Such a goal will keep the user on track for experiencing serendipity, and help us answer the question, "Why does the user add mental and cognitive workloads?" As we study and implement various user controls, visualizations, and transparency in serendipity-oriented recommender systems, we must keep in mind the cognitive workload imbalances for the user. What is the cost of this endeavor? That is, what is the mental workload of the user when attempting to obtain serendipity? It is assumed that this kind of operation must come at some mental or physical cost, which should be kept in mind before creating these systems and using them. In other words, serendipitous recommender systems might create some opportunities, but they might create problems too. User control (UC) and serendipity have been studied in experiments and proved successful. We assume that a high workload is associated with a decrease in performance and that detours from one's mission should not be an option, especially when serendipity is expected. As we conduct more tests on user interface–based serendipity, we must calculate whether there are workload-related problems associated with it. Our aim is to reveal the hidden costs.

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Previous research has focused on serendipity via user interface in recommender systems and has aimed at increasing the behavioral data to learn more. In this study, our objective is to promote recommender systems for use in study. Such systems can be helpful when specific cases are interesting for theses or final-year projects. We experimented with various interactive recommender systems that facilitated serendipity for users. These users were mostly university students. In this article, we pose some key questions and reveal some important discoveries. First, users have specific preferences when they want to evaluate serendipitous recommendations on user interfaces, or we could say, when they want visualizations for serendipity [1]. Second, user controls can be used to facilitate serendipity of recommendations [2]. Third, university-level students want serendipity in their research, but instructors tend to want recommender systems to point students in particular courses. Serendipity is not well studied in academia [3]. Serendipity-based recommenders can be research tools (Afridi, Yasar, & Shakshuki 2019). Similarly, serendipity, when used in research, can be helpful for university instructors (Afridi, 2019). Further transparency in recommendation systems can be helpful for connecting ideas and facilitating serendipity (Afridi, 2019). Studies of triggers and connection-making for serendipity [4] have also provided an opportunity to investigate interface designs for serendipity-focused operations in recommender systems (Fig. 1).

In this work, we review research that has been done in the costs of using conventional recommender systems and provide a reference on how user interfaces should be designed to reduce cognitive load and increase chances of serendipity. Our study also reveals the cognitive workload on student users associated with accuracy-oriented recommender systems. This work also strengthens our understanding of previous work on serendipity through user-interface designs. When working on user-interface–driven serendipitous recommenders, it is necessary to know the factors acting on users

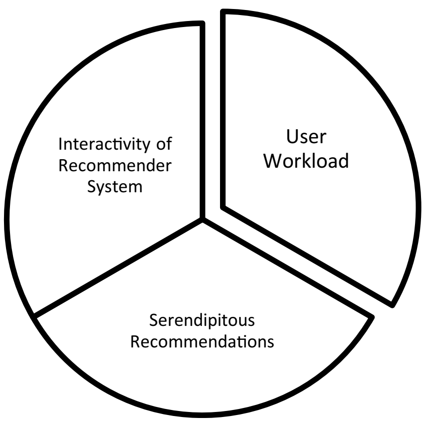


Fig. 1 Research focus in recommender systems

who are open to experiencing serendipity. Therefore, the main question driving this research is how a serendipity-facilitating recommender will affect users' cognitive workloads. Will it have implications for how users interact with the recommender system with a user interface that was not specifically designed for serendipity? And will it increase the serendipity-related workload? Do we need to design new user interfaces for commercially available recommenders for academia when serendipity takes roots in academic systems? We believe that when serendipitous systems are encouraged, studies will be needed to evaluate the commercially available recommender systems. Recommender system development should keep all these aspects and their costs in mind.

1.1 Topic overview

Cognitive workload increases when one seeks serendipity through user interfaces [4]. This reveals some problems related to how recommenders are not generally designed for serendipity. It also shows the limitations of current commercially available recommender-system user interfaces. We want to investigate this topic further by looking at more commercially available recommenders. This research should help us inform design decisions with respect to recommender-system user interfaces based on subjective evaluations. In academia, introducing serendipity as a concept for improving research and study has difficulties. It is important to study how user workload is affected for students who use serendipitous recommender systems for their work. We need to know more about the workload ratio at play using such systems. User controls are an important component of a recommender system. He, Parra, and Verbert (2016) showed that there are few studies on user interface and serendipitous recommenders, however, user-control studies, on the other hand, have already taken a dominant position in recommender-system user-interface research [5]. In Figs. 2, 3, 4, and 5, we present four recommender systems used in academia that were studied for task load during serendipity-related operations.

This work presents several contributions to the design of user-interface–based serendipity-facilitating recommender systems. It helps us understand the cognitive workload associated with recommender systems used in academia and whether serendipity is achieved using these systems, and if so, what the composition of the relevant user interface is. This work will also help us understand the academic environment that is critical to developing serendipity-oriented recommender systems. Finally, this work will also help us understand the weaknesses associated with accuracy-oriented recommender systems, so that those can be mitigated in the development of serendipity-oriented systems.

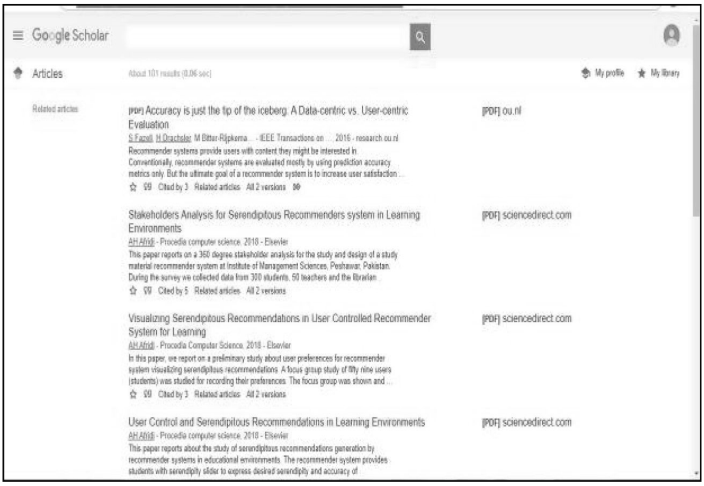


Fig. 2 Google Scholar

2 Related work

Recommender systems' user interfaces have been widely studied for task load. One scale used for measuring task load is the NASA task load index (NASA-TLX), a research instrument used to collect data from users on workload. In a related work, we present NASA-TLX studies carried out for user interface in computers and for recommender-system user interfaces. We also provide analyses of the literature and subjective evaluations. Recommender systems have been a focus of research for years, and many researchers have shown them to be a rich research investment. Recommender system have been thoroughly studied for technology-enhanced learning [6]. Learning sciences are harnessing the potential of recommender systems. Ever since recommender systems first gained attention [7], they have grown in importance, through both the pre- and post-big data eras, particularly in computer sciences. The research has put a high emphasis on working on the front end, middleware, and back end of recommender systems to facilitate serendipity. We discuss the user interfaces of recommender systems and various dimensions of them such as serendipity and interactivity.

By putting users in control, a study can tell us about the importance of user control in the operations of recommender systems [8]. He et al. [9] discussed in detail the dynamics of interactive recommender systems. Their study examined recommender visualizations, user controls, transparency, and context-related issues, and they described the implementations and the broader details of each kind of implementation. Their study revealed the need for serendipitous recommender systems with interactive aspects. Yet as we look at recommenders' attributes one by one, we find no studies describing their mental-workload impacts on users.

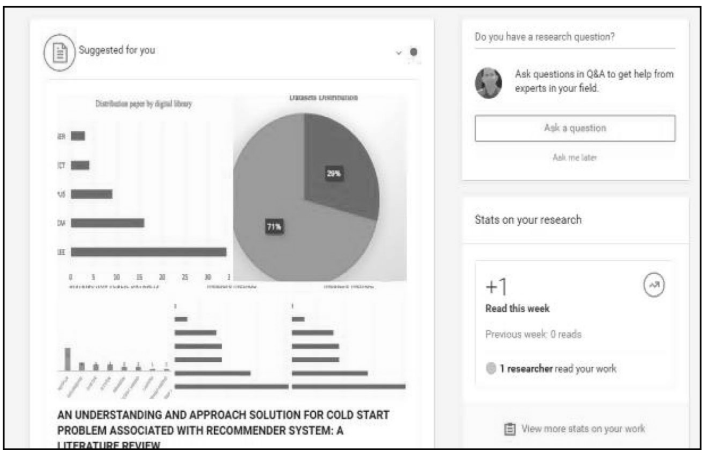


Fig. 3 ResearchGate

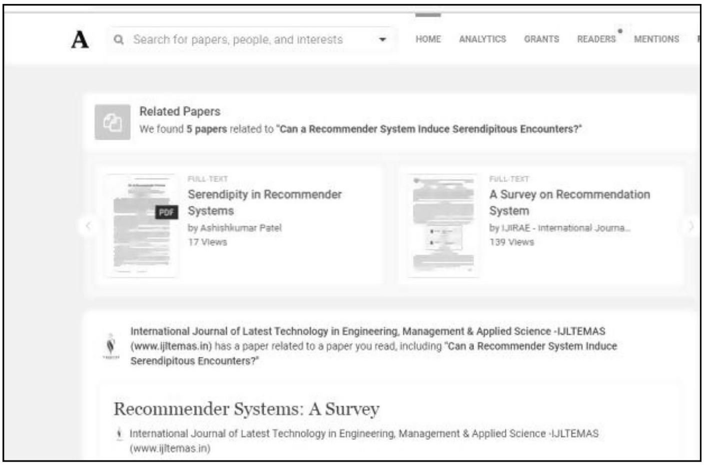


Fig. 4 Academia.edu user interface

The set fusion project by Verbert et al. [10] is a pioneering, state-of-the-art work that shows how visualizations and interactive interfaces can boost the applications of recommender systems. Similarly, controllability is a pioneering field of work in interactive recommendation systems that shows the importance of user controls and visualizations to the adoption of those systems [11]. A study on the interactivity of recommenders by Jugovac and Jannach [12] also showed the importance of interactivity in HCI-driven applications and reinforces our questions about the impact of interactivity on user workload.

Serendipity in recommender system has gained attention over the years. Algorithmic and user-interface approaches have been studied, as we discuss in the following section, and have proven to be a potential information-referral strategy in academia and applied computer science. The existence of serendipity in scholarly papers [13] and a survey of serendipity by Kotkov, Wang, & Veijalainen (2016) show how serendipity as an aspect of recommender systems is getting attention from researchers hoping to make architectural changes to their design and implementation.

We narrow down our discussion of the literature to two topics: user-interface studies through the lens of NASA-TLX and user-interface studies for recommender systems from NASA-TLX perspective on task load.

2.1 User interface studies and NASA-TLX

Yiyuan et al. [14] explained how accidents can be avoided when flight-deck designs are being evaluated and studied for human behavior during flight. They reported that according to NASA, 75% of accidents are related to human performance. The authors briefly discussed SWAT and other methods of evaluation and advocate for the NASA-TLX method. They argued that by considering human factors, one can reduce the unnecessary costs of developing aircraft.

Cao et al. [15] provided a comprehensive overview of how NASA-TLX has been used over the years. They explained

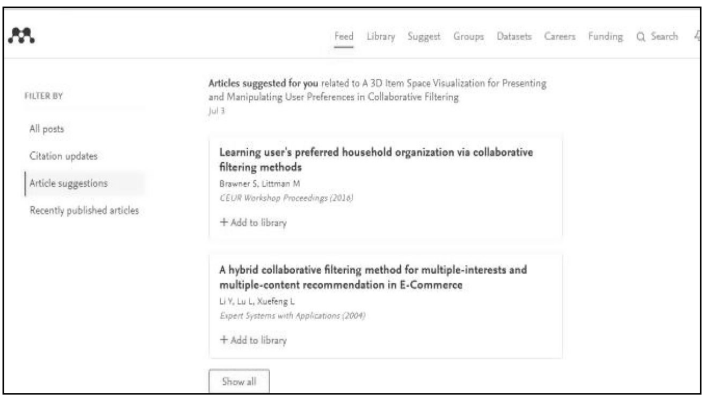


Fig. 5 Mendeley user interface

how various psychological metrics have been used to evaluate user workload and its mental implications. Their article provides a design for applications that can be used as an approach to NASA-TLX data collection.

GOMS (goal, operations, method, and selection) and NASA-TLX have proved to be an effective combination for HCI (human-computer interaction) evaluation, as discussed by Ramkumar et al. [16]. These authors described the relationship between GOMS and NASA-TLX and suggested some HCI designs. They briefly discussed various HCI evaluation techniques and the variations of NASA-TLX. NASA-TLX was used in their study to detect and evaluate workload during image segmentations. GOMS and NASA-TLX were used on the system during a radiotherapy session. The authors concluded by making some design suggestions for interactivity and recommending further study of input devices and more subjective studies.

Alsuraykh et al. [17] provided insights into the connection between stress and mental workload. The authors discussed stress and strain and their impacts on users' performance. Relying on the transactional theory of stress, they assumed that people feel stress when there is a mismatch between task demand and task resources. They reported that other techniques, such as measuring physical parameters of the human body, have been used to detect stress. They concluded by emphasizing the need for more research on stress and mental workload. Sharek [18] discussed an online tool for the application of NASA-TLX for researchers. Rizzo et al. [19] studied workload comparisons using NASA-TLX and work profiles. They presented a novel mechanism for modeling and assessing mental workload. The method is flexible and promising.

Robot and crane interfaces have benefitted from NASA-TLX. Chi et al. [20] researched a crane that uses augmented-reality guidance and shows an increase in mental workload. Scholtz, Antonishek, and Young (2004) used NASA-TLX to develop human-robot interaction guidelines. Whittington [21] examined autonomous transportation systems, focusing on a wheelchair system that was evaluated according to the SUS (system usability scale) and NASA-TLX, to study user-system interactions. The study addressed head-based and touch-based interaction techniques and described how different techniques increase and decrease mental and physical demands.

2.2 Recommender system studies and NASA-TLX

Recommender-system studies have also benefited from NASA-TLX. Many case studies have indicated the usefulness of NASA-TLX for human-recommender interface problems and their implications for users. Here, we briefly discuss several important studies that highlight these aspects. Veas and Di Sciascio [22] studied the exploration of cultural collection in recommender systems. They showed various visual mechanisms for achieving lowering workloads. Di Sciascio, Sabol, and Veas (2015) studied recommender-system interfaces that enable exploration, in a study directed toward a user-controlled approach. A visual recommender system helped users operate with low cognitive loads. NASA-TLX was used to evaluate the user interface for multiple tasks.

Machado et al. [23] studied a game-design–assisting recommender system (Pataki) through NASA-TLX. The recommender was meant to reduce workload. The authors reported on the use of NASA-TLX with respect to workload and PANAS for computational load. Albanese et al. [24] studied the effective browsing of multimedia recommendations. NASA-TLX was used to study mental workload. Their proposed system provided a better user experience. Amato et al. [25] studied a multimedia art recommender system and used NASA-TLX to calculate the workload for users. Dominguez et al. [26] studied the explanations and accuracy of recommendations, using NASA-TLX to study the cognitive load on users. Albanese et al. [27] studied a multimedia recommender system, Picasa, which was evaluated through mouse clicks and time (objective variables). The system was also evaluated for mental, physical, and temporal demands using NASA-TLX (Tables 1, 2, 3, 4, 5, and 6).

In a study of stress among car drivers, Sugiono, Widhayanuriyawan, and Andriyani (2018) found that both objective evaluation and subjective evaluation (via NASA-TLX) produced the same results. City driving resulted in higher stress than expressways or rural roads. NASA-TLX also indicates the same stress levels as were detected by heart monitoring devices.

Lowndes et al. [28] used NASA-TLX to study workload in surgeons. As new technologies become available to surgeons, it is imperative that the mental and workload costs they incur be evaluated. The specialties involved in the study included general, colonic, and plastic surgery. The study was instrumental in revealing the high physical and mental demands of various surgical procedures. Hoonakker et al. [29] also used NASA-TLX to study workload in the medical field, focusing on nurses. They showed the effectiveness of NASA-TLX for measuring the healthcare workload of nurses in intensive care units. Gutiérrez et al. [30] studied augmented health applications using the technology acceptance model (TAM) and NASA-TLX scales. An augmented realty (AR) system's performance was evaluated and found to be suitable for care situations in certain configurations. NASA-TLX provided an good platform for computing the workload of such AR systems. Poor laparoscopic performance was observed by Yurko et al. [31] for its potential to cause high mental workload. The authors used NASA-TLX to study the impact of laparoscopic equipment. They found that the potential for error increased with high mental demands. Longo and Kane [32] studied an electronic record system's user interface, using NASA-TLX

Table 1 Recommender systems and user interface impact on workload

Research study	Recommender system	Tests and evaluation metrics	Impact
Veas and Di Sciascio [22]	Tagbox and Rank View–based system	NASA-TLX, ANOVA	Lower workload when using uRank
Di Sciascio et al. [22]	uRank visual tool	NASA-TLX, ANOVA	uRank incurs lower workload
Machado et al. [23]	Game assistance recommender system	NASA-TLX, one-sided Wolcoxon Whitney Test	Decreased workload levels
Albanese et al. [24]	Multimedia recommender for repositories	NASA-TLX, difference in averages	Improved performance, outperforms Picasa
Amato et al. [25]	Recommender for multimedia art collection	NASA-TLX	Improved performance
Dominguez et al. [26]	Recommender system for arts	NASA-TLX, average, SEM	Explainable interfaces preferred by users

to assess workload. Their results showed that repeated use of the system increased mental workload, which could directly affect patient care at the hospital.

Transportation systems have also benefited from NASA-TLX systems. Partala and Salminen [33] evaluated a photorealistic map that runs on a mobile platform. Their tests revealed that the street-view layer created a higher task load. In a similar study, Riener and Thaller [34] used NASA-TLX to assess a driving simulator to better understand human error in driving and learning, and the causes of different accidents. Their study has helped researchers gain insights into driver–vehicle interfaces and to deliver subliminal information. Such information will be applied in future vehicle-interface design and development.

Chemistry education and ease of use for learning through computers were studied by Fjeld et al. [35] using NASA-TLX and the software usability measurement inventory (SUMI). Grigg, Garrett, and Benson (2012) studied problems in engineering, with a focus on problem-based learning for engineering students. NASA-TLX was used to gage students' perspectives on task difficulty. Riccio et al. [36] studied workload measurement for human-computer interfaces. They focused on people with disabilities and their special interaction needs for computers. Their study highlighted the importance of subjective evaluation when opportunities for objective (technical) evaluation are weak. Aslan et al. [37] studied users' cognitive status during a specific user-interface activity with 24 participants. They used NASA-TLX to assess tasks such as drop-and-drag. A study of ATMs by Regal et al. [38] used NASA-TLX and the SEQ (single easy question) and TAM scales. They compared three workflows: ATM-based, phone-and-ATM–based, and phone-only transactions. Phone-based transactions were preferred for their low workload in spite of their lower security.

Table 2 User interface capabilities

User interface capability	Functional service
Button	Re-rank recommendations
Drop-down list	Selection and presentation of recommendations
Scrolling list	Selection and presentation of recommendations
Radio button and checkboxes	Filters and restrictions
Function transparency box	Following a researcher or influencer

3 Cognitive load and recommender systems

Understanding the costs and benefits of user-interface–driven serendipity operations and workload-related stress is of utmost importance. We elaborate on the costs, benefits, and compromises in user-interface designs in the following section.

3.1 Cost and benefits

What happens when no consideration is made of workload in the design of a serendipity-oriented recommender system? These systems must provide a user interface that facilitates serendipity, but there could be situations that dissuade users from the course of serendipity or create stress for them that might hurt performance. Second, it is possible that user-interface–induced serendipity increases physical workload through

Table 3 NASA-TLX scale

Reading scales of NASA-TLX	Range (Low = L, High = H) (Min = 0, Max = 20)	Explanation
Mental demand	L to H	Scale for mental workload
Physical demand	L to H	Scale for physical workload
Temporal demand	L to H	Scale for temporal workload
Performance	L to H	Scale for user performance
Effort	L to H	Scale for user effort
Frustration	L to H	Scale for user frustration

Table 4 Recommender system facilitating serendipity and probability of impact

Components	Placement	Type of potential impact
User control	User interface	Physical load
Transparency	User interface	Mental load
Context	User interface/inference engine	Mental load/frustration
Serendipity	User interface	Performance/mental load

repeated questions or adjustments to user controls. Third, the connection-making that these systems facilitate could increase workload and create a ripple effect of frustration and effort for users. The user workload might be captured and embedded in the transparency function of the recommender to provide users with feedback on the workload. Therefore, user-interface designers must consider the physical and mental workloads involved when they are designing user interfaces that can facilitate serendipity.

3.2 Compromises in interactive recommender systems for serendipity

The research we discussed in related work consisted of two kinds of recommender-system user interfaces: those that are designed to facilitate serendipity and those that are not but are used to do so. Both types can produce different workloads for the same tasks. Therefore, we must focus on user-interface design and the results of testing them for human workload information. In the learning sciences, students might accept a user interface that uses serendipity for its esthetic value, but it might not be suitable for the long term. Similarly, user interfaces that facilitate serendipity could have low task loads for both serendipity- and accuracy-oriented recommendations. It is therefore important to investigate both types of interface.

4 Study design

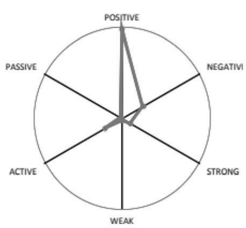
This study examines the user interfaces of four academic recommender systems for their respective workloads: Mendeley, Google Scholar, Academia, and ResearchGate. The students who participated in the study were asked to find a topic for their final research thesis using the recommenders and to evaluate and observe the recommenders. They were given 2 weeks to prepare for and complete this task. A questionnaire was then given to them in class. The NASA-TLX questionnaire was used for weighted data. Our overall impression was that most of the students used Google Scholar; however, the graduate students were more aware of the use of recommenders for topic selection. Our research differs from previous studies of serendipity by focusing on recommender systems for academic research and using a broad range of recommenders. We also performed statistical tests (described in the next section) to find answers to our research questions. This research will

Table 5 Users sentiments for first dataset collection (complete data set)

RESULTS

ATTITUDE GROUP

Category	Grade	Value	Words	Highlighted words
POSITIVE	VERY HIGH	100	15	better, content, desire, easy, even, fair, good, helpful, interesting, open, productive, proper...
NEGATIVE	NORM	28	8	bad, difficult, lacking, little, need, problem, stressful, wrong
STRONG	LOW	11	11	accomplish, achieve, full, improve, lot, more, most, productive, recommendation, require, searc...
WEAK	VERY LOW	2	2	little, need
ACTIVE	NORM	22	14	accomplish, achieve, better, get, improve, make, open, representation, require, research, searc...
PASSIVE	VERY LOW	1	6	attention, content, desire, need, related, value



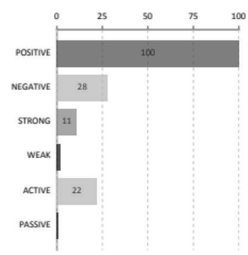
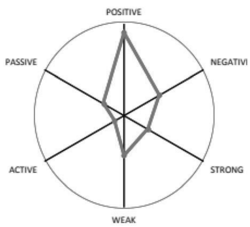


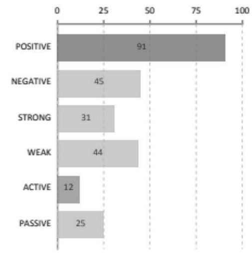
Table 6 User sentiments for second dataset collection (complete data set)

RESULTS

ATTITUDE GROUP

Category	Grade	Value	Words	Highlighted words
POSITIVE	HIGH	91	9	better, even, fair, good, help, improvement, relevant, simple, understandable
NEGATIVE	NORM	45	5	bad, complicated, difficult, hard, need
STRONG	NORM	31	7	full, improvement, knowledge, more, much, search, still
WEAK	NORM	44	2	help, need
ACTIVE	LOW	12	11	animation, ask, better, compare, do, get, improvement, representation, search, send, work
PASSIVE	NORM	25	6	hard, like, need, quit, related, want





help mitigate the cost of deploying serendipity-facilitating user-interface–driven recommender systems. We present recommender-system evaluations and discuss the participants, sample size, and selection criteria for evaluating the recommender systems (Fig. 6).

4.1 Research questions

1. What trends do users find in experiencing serendipity while using Google Scholar, Mendeley, Academia, and ResearchGate?
2. Do these recommender systems create serendipitous recommendations for users?
3. What are the implications of cognitive workload?

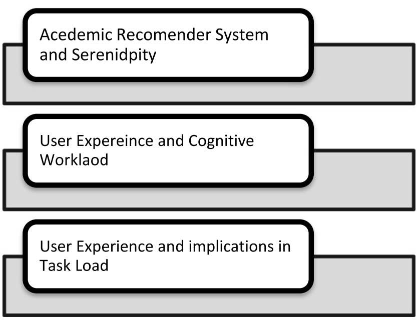


Fig. 6 Investigation diagram

5 Experiment

This research was conducted by repeatedly measuring students' experiences. We measured serendipity with a questionnaire on ResQue by Pu. et al. and used NASA-TLX to measure cognitive load on users. The study was conducted on graduate and undergraduate students at the Institute of Management Sciences in Peshawar, Pakistan. The repeated-measurements approach was taken because it was the best suited to study serendipity of recommendations and NASA-TLX for cognitive load. We also interviewed users to confirm our findings.

We evaluated the user interfaces of four recommender systems that are available online: Mendeley, Google Scholar, Academia, and ResearchGate. These systems take various inputs, such as keywords, papers, search items, or topics, and provide relevant recommendations aligned with accuracy of recommendations. Because these systems are not specifically designed for serendipity, it cannot be ruled out that serendipitous recommendations will not appear. We asked users to evaluate the user interfaces by trying to find research topic. The selection of a topic as a result of a recommendation was termed a serendipitous encounter. If the user was unsuccessful in finding serendipitous recommendations, this was recorded. Users were then asked to weigh the NASA-TLX and then revisit their recommender and results, and then to fill in NASA-TLX ratings for each recommender system. Scores were recorded, and statistical tests were conducted to assess the task load on each user by each system. Normally, we evaluate recommender systems through the work of (Pu, Chen, & Hu, 2012). The participants' backgrounds are summarized below. The education level was undergraduate and graduate. The time spent on using these recommenders was 2 weeks. The task that was categorized as serendipity was the selection of a thesis or final project from the recommendations. Both male and female students from the Peshawar, Pakistan region took part. The topics included project management, computer science, and public administration. The procedure of the usability test for all four recommender systems is described in Fig. 7.

6 Results

We present the results of our study. As described above, we collected data on students' use of these recommenders for 2 to 3 weeks. Data were collected using Zoho online forms. The form consisted of a questionnaire composed our ResQue model and NASA-TLX. Appropriate scales were used to collect data. Serendipity, transparency, usefulness, and context were studied using the ResQue model–based questionnaire. The NASA-TLX questionnaire was used to detect pressure, irritation, mental and physical stress, and physical activity. Participants answered the questionnaire call and submitted forms online, and the data were saved in CSV format (comma-separated values) for analysis in Microsoft Excel.

We collected the data in two phases ("first read" and "second read") for repeated measurement. Both times, the data consisted of students' evaluations of the recommender systems on forms based on the ResQue model and NASA-TLX. The data from the two collections differed in size. We performed discriminate analysis on both data sets and sentiment analysis on the comments about recommender-system usage [39]. The participants were bachelor of science students in software engineering and master's students in computer science from the Institute of Management Sciences in Peshawar. The students were asked to enter their responses in the forms after using the recommender systems. Nearly 2 weeks passed between the two data collections. Most of the students were 18–25 years old. The students selected were working on their final-year projects and theses, so they had an understanding of recommender system usage.

6.1 Data calibration

The questionnaire used two scales to quantify user experience, NASA-TLX and a ResQue-based questionnaire. Because NASA-TLX uses a scale of 20 and ResQue uses a five-point Likert scale, we divided the values received by 20 and 5, respectively.

6.2 Data validation

The data were validated via online data reception and stored in a Microsoft Excel spreadsheet.

6.3 Full dataset

The complete dataset consisted of 42 responses in the second read and 69 in the first. The data were filtered as described in the following section. The full dataset had problems, such as inconsistent responses, so for equal datasets, repeated measures were taken.

6.4 Filtered dataset and tests

The data were filtered for users whose responses were present in both collections. This filtered subset was analyzed for consistency, for the presence of values related to serendipity of recommendations, and for overall impact. Each read contained 17 responses.

The Wilcoxon Signed Ranks Test (a non-parametric statistical hypothesis test used to compare related samples, matched samples, or repeated measurements on a single sample to assess whether their populations' mean ranks differ—i.e., a paired difference test) and the Kruskal Wallis Test (a nonparametric analog of ANOVA) provided a comparison of

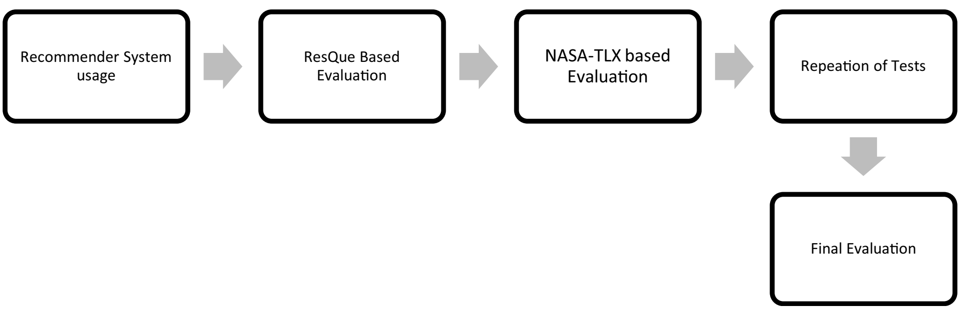


Fig. 7 Procedure of usability test

parameters in dependent and independent samples of small sizes. The analysis is given below.

1. Significant differences in the question "How irritated, stressed, and annoyed versus content, relaxed, and complacent did you feel during the task?" were discovered. In the second read, the estimates on a scale were higher. This differences provided by changes in estimation of ResearchGate system. There are no differences in responses for this question across systems in the first and second reads.
2. Significant differences in the question "The recommender provides an adequate way for me to express my preferences" were discovered. In the second read, the estimates on a scale were lower. These differences provided by changes in estimation of ResearchGate and Academia.edu systems. There are no differences in responses for this question across systems in the first and second reads.
3. Significant differences in the question "The recommendations are Useful for me" for Google Scholar were discovered. In the second read, the estimates on a scale were lower.
4. Significant differences in question "How much time pressure did you feel due to the pace at which the tasks or task elements occurred? Was the pace slow or rapid?" for Academia.edu were discovered. In the second read, the estimates on a scale were higher.
5. In the first read, there are significant differences in the question "The recommendations are Useful for me?" across systems. Ranks for Google scholar are higher than Research Gate and Academia.edu. Estimation for them are equal.
6. In the first read, there are significant differences in question "The items recommend to me tool my personal context requirements into consideration?" across systems. Ranks for Academia.edu are principally higher than median and ranks for Research Gate are lower than median.
7. There are no differences in responses for every question across systems in second reads.

6.5 Discriminant analysis for the first and second reads

6.5.1 Discriminant analysis for first read

The discriminant chart for the first collection is shown in Fig. 8. The recommenders shown are Mendeley, Google Scholar, ResearchGate, and Academia. The chart shows substantial differences in experience created by all four systems. Similarly, the chart for discriminant analysis for the second collection in Fig. 9 shows different experiences for all four systems being reported by users.

6.5.2 Discriminant analysis for the second read

The analysis of data from both collections revealed users' experiences of the recommender systems. The

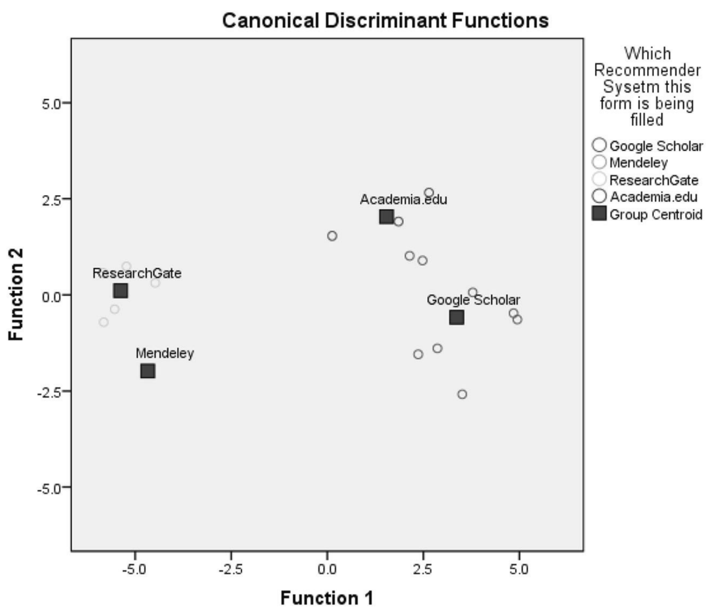


Fig. 8 Discriminant analysis for recommender system for the first read

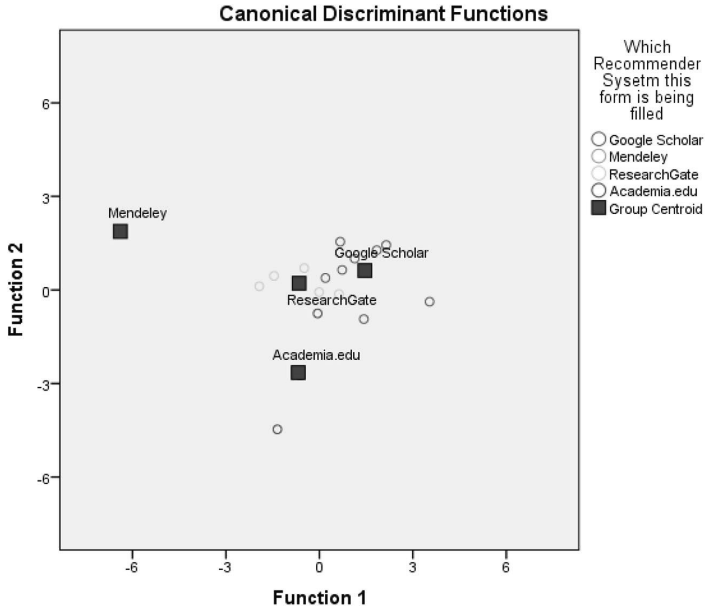


Fig. 9 Discriminant analysis for recommender system for the second read

major limitation of this work is the sample size, due to the sparse responses. Although a detailed impression based on the users' feedback is described in the annexure, the overall impression given by the tests is that these recommender systems do not facilitate serendipity, though users have the occasional serendipitous experience. The data also show more responses involving Google Scholar and associated serendipity experiences. This might be due to the rich user controls of that system, or to large lists of recommendations, which might create a greater chance of a serendipity trigger. The overall impression was also that academic recommender systems do not provide users with an option to seek serendipity (Figs. 10, 11, 12, and 13).

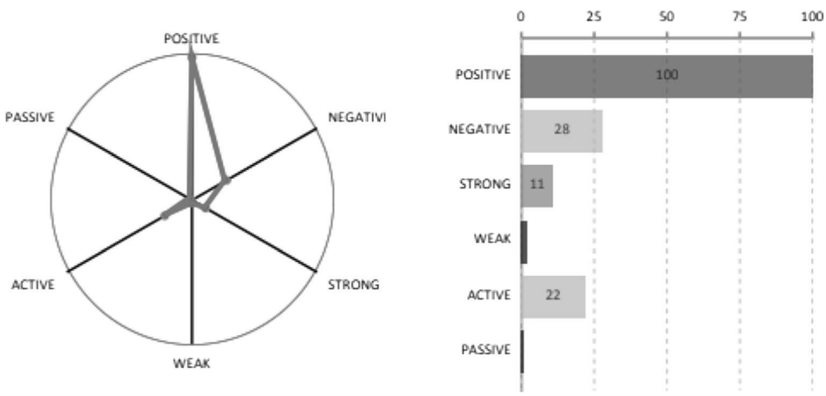
7 Discussion

In this section, we discuss the results of the statistical tests conducted on the data. These results are analyzed in view of the research questions about recommender systems, serendipity, and cognitive load.

7.1 What trends do users find in experiencing serendipity while using Google Scholar, Mendeley, Academia, and ResearchGate?

The user-interface design of these recommenders varies. The significance values show that all four create a significant difference level of mental and physical load. There are also

Fig. 10 The sentiment analysis of all four recommender user experience for first dataset collection



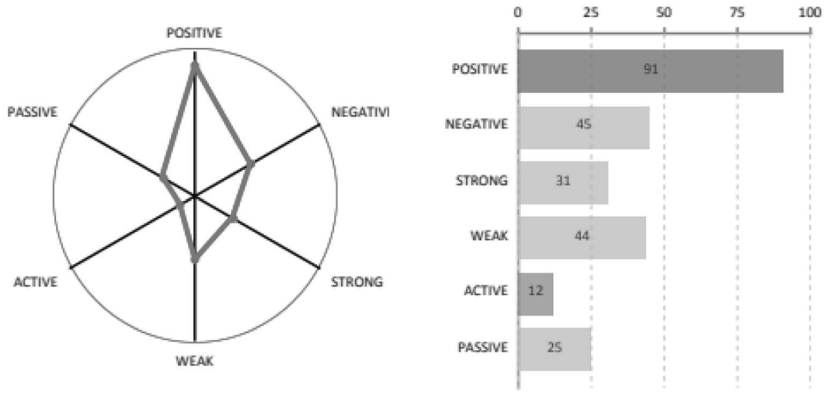


Fig. 11 The sentiment analysis of all four recommender user experience for second dataset collection

significant differences in mental perceptual activities among the four. Their usefulness does show significance, so there is a higher chance of usefulness, serendipity, and mental workload associated with each recommender's user-experience design.

7.2 Do these recommender systems create serendipitous recommendations for users?

There is significant serendipity facilitation and experience in the recommender systems. The user-interface designs vary; Google Scholar has most user controls and list-based outputs, whereas Mendeley, ResearchGate, and Academia have a relatively minimal user controls.

7.3 What are the implications of cognitive workload?

As serendipity and usefulness of recommendations are sought-after features, getting them through user controls can increase the mental and physical workload on the user. Although this may depend on the design, we can say that the chances of performing well academically can be expected to improve if the mental or physical workload increases drastically at the cost of serendipity. We therefore conclude that the task load can influence the user's performance in terms of mental and physical work needs. At the same time, user interfaces have not been specifically designed for that purpose. We therefore conclude that there are many factors to study before we can find a design that balances serendipity needs with mental stress limits for performing expected work.

8 Conclusion

In this work, we find that diverse task loads are associated with the recommender systems used in academia. We need to develop an approach and design methods that cater to the needs of users for serendipity-facilitating interfaces. At the same time, there are mental and physical workload stresses associated with users' attempts to find serendipitous recommendations. We studied the task load associated with introducing serendipity to recommender systems, and though our focus was on user-interface–driven serendipity of recommendations, more studies are needed on recommender-system design and its associated cognitive workload. This study was designed on the principle of repeatedly recording students' experiences and performing sentiment analysis on the datasets. The data were collected through electronic questionnaires and from graduate and undergraduate students. The questionnaires were based on NASA-TLX and ResQue and designed to capture various attributes of recommender systems, especially serendipity.

Several attributes showed significant difference in user opinion, such as experience of serendipity, mental, and physical work needed to operate the recommender, and usefulness of recommendations. It was found that conventionally available recommender systems might occasionally facilitate serendipity, but there are already problems with user control over recommendations and the associated cognitive workload. This suggests the development of more user-friendly systems and serendipity-facilitating experiences.

Users experienced relativity low control and moderate mental and perceptual activity load in this study. In addition, a moderate level of physical activity was required by all four recommender systems. Moderate physical activity was also reported in the data.

8.1 Questionnaire link

https://forms.zohopublic.com/imsciences/form/QuestionnaireforRecommenderSystemUserInterfaceEval/formperma/zbYK0Y63dKdkLHHFo2Hhl6pAENgRLEVOqEs-2B5Pu3U

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ANNEXURE-I

Table 7 Descriptive statistics

	N	Mean	Std. deviation	Minimum	Maximum
How much mental and perceptual activity was required? Was the task easy or demanding, simple or complex	16	.4656	.24339	.15	.85
How much time pressure did you feel due to the pace at which the tasks or task elements occurred? Was the pace slow or rapid?	16	.4594	.25313	.05	.85
How successful were you in performing the task? How satisfied were you with your performance?	16	.4031	.22470	.05	.80
How hard did you have to work (mentally and physically) to accomplish your level of performance?	16	.4531	.24931	.15	.80
How irritated, stressed, and annoyed versus content, relaxed, and complacent did you feel during the task?	16	.4719	.24628	.05	.80
The recommendations are useful for me	16	.6500	.17127	.40	1.00
The recommendations are surprising to me	16	.5875	.17078	.40	.80
The recommender provides an adequate way for me to express my preferences	16	.6375	.16683	.40	.80
The items recommend to me tool my personal context requirements into consideration	16	.6375	.16683	.40	.80
The system helps me understand why the items were recommended to me	16	.6125	.17078	.20	.80
How much mental and perceptual activity was required? Was the task easy or demanding, simple or complex Second read	16	.4531	.23271	.15	.85
How much time pressure did you feel due to the pace at which the tasks or task elements occurred? Was the pace slow or rapid? Second read	16	.4906	.23468	.15	.85
How successful were you in performing the task? How satisfied were you with your performance? Second read	16	.3844	.19470	.10	.70
How hard did you have to work (mentally and physically) to accomplish your level of performance? Second read	16	.4906	.19427	.10	.80
How irritated, stressed, and annoyed versus content, relaxed, and complacent did you feel during the task? Second read	16	.5375	.22620	.10	.85
The recommendations are Useful for me Second read	16	.6250	.14376	.40	1.00
The recommendations are surprising to me Second read	16	.5125	.17842	.20	.80
The recommender provides an adequate way for me to express my preferences Second read	16	.5375	.14083	.40	.80
The items recommend to me tool my personal context requirements into consideration Second read	16	.5875	.15438	.20	.80
The system helps me understand why the items were recommended to me Second read	16	.6500	.20000	.40	1.00

ANNEXURE-II

Complete dataset analysis.

Wilks' Lambda for the first data set is given below.

Table 8 Wilks' Lambda

Test of function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 3	.484	43.864	33	.098
2 through 3	.685	22.865	20	.295
3	.854	9.537	9	.389

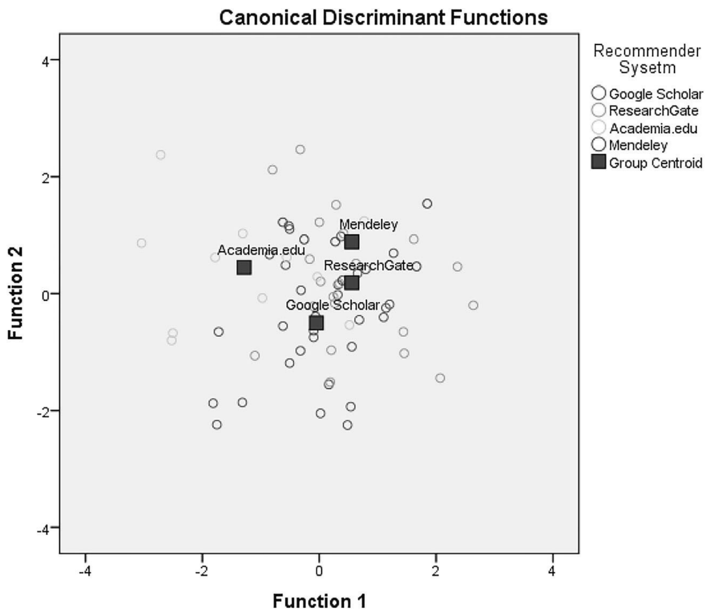


Fig. 12 Discriminant analysis of all four recommender systems

Wilks' Lambda for the second dataset is given below.

Table 9 Wilks' Lambda

Test of function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 3	.383	32.183	33	.508
2 through 3	.723	10.873	20	.949
3	.918	2.882	9	.969

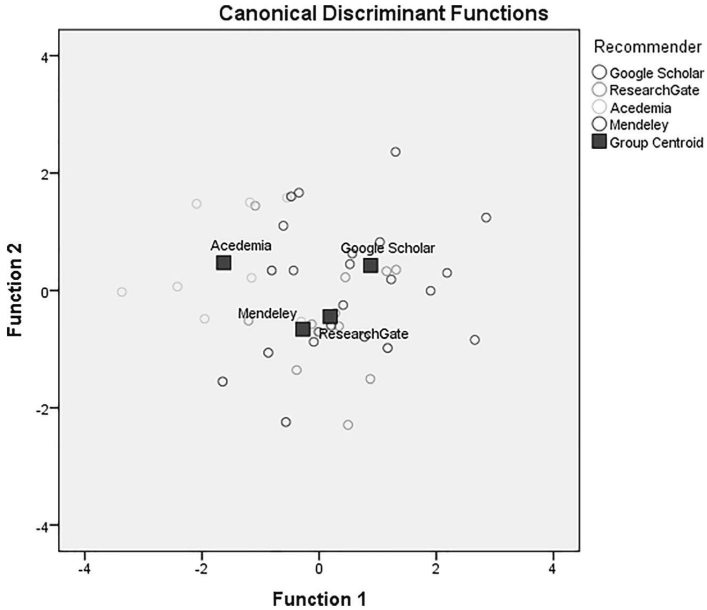
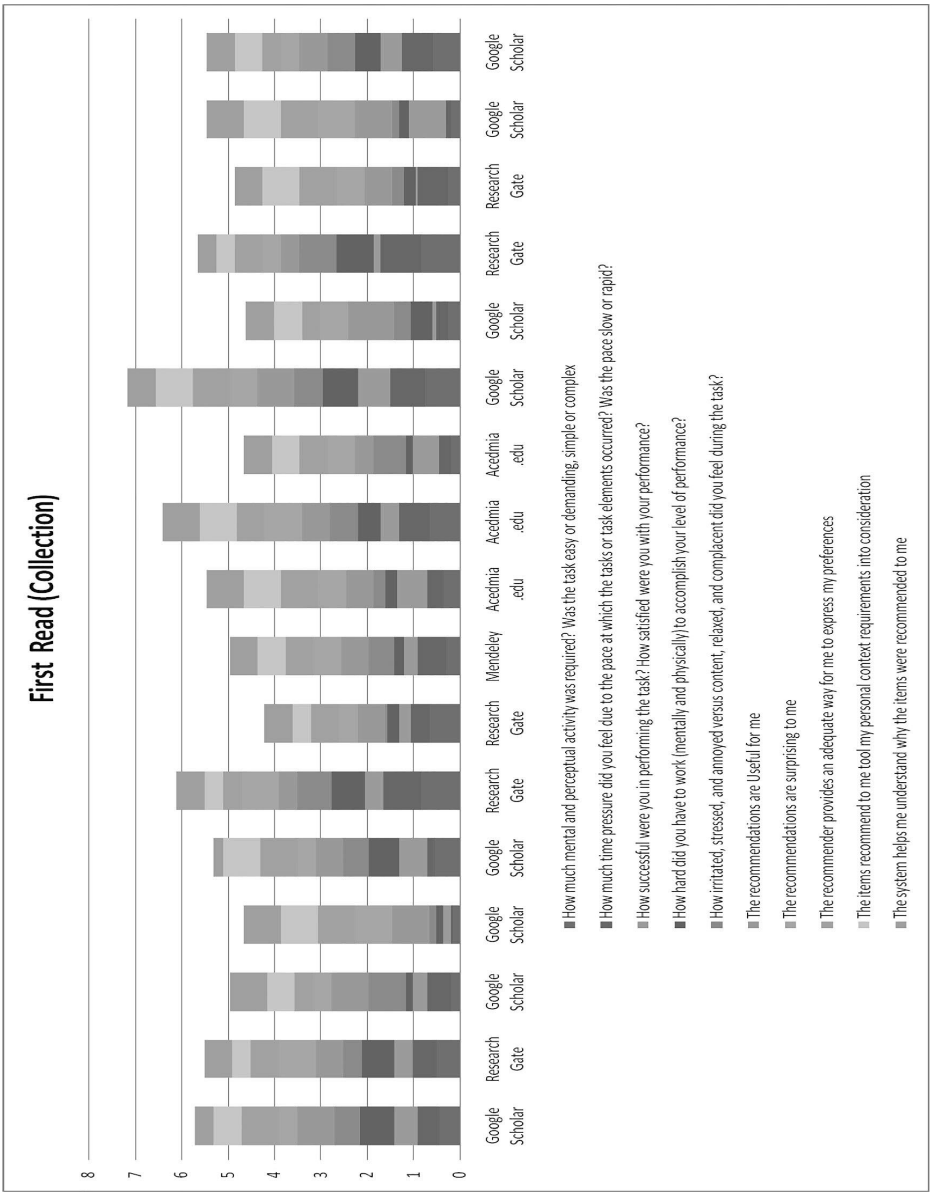
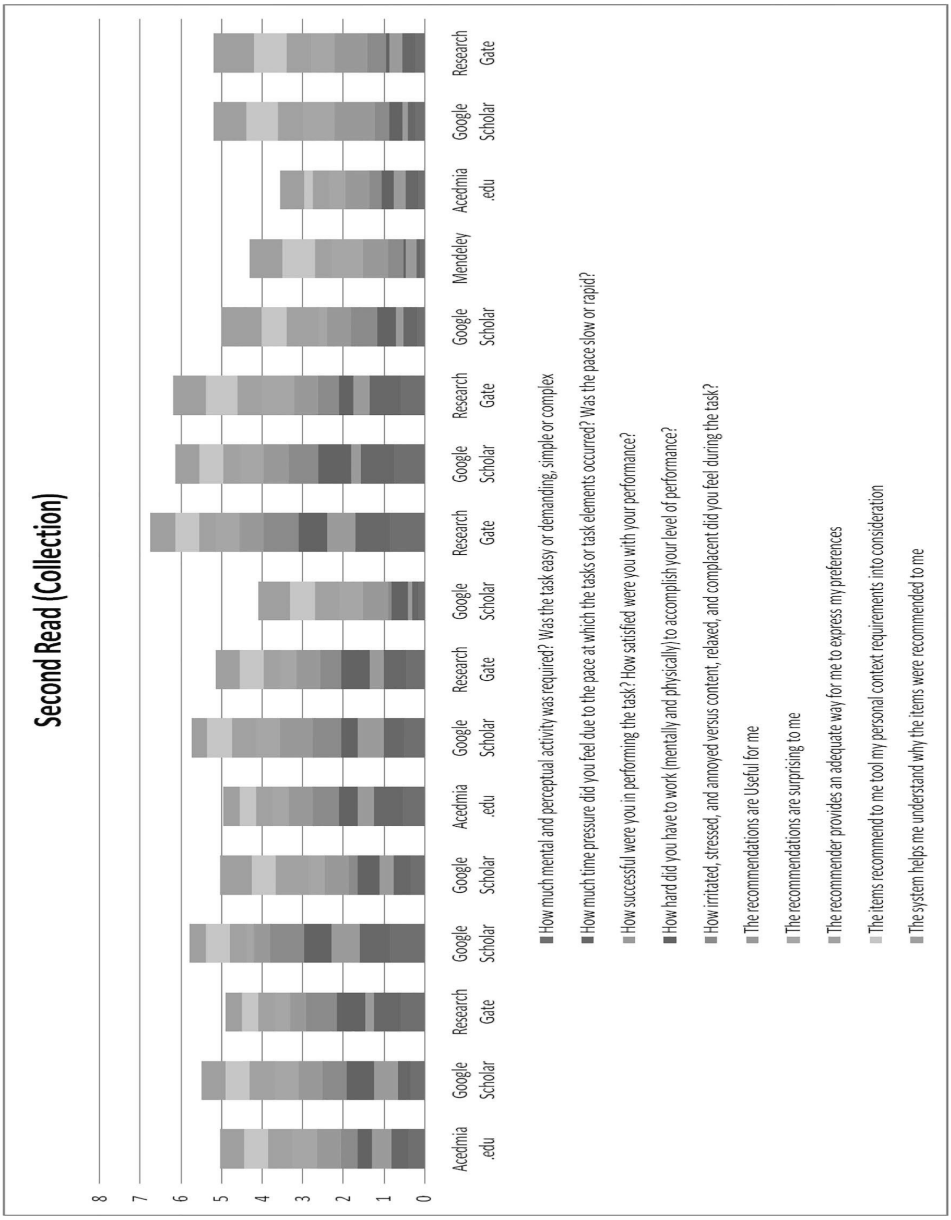


Fig. 13 Discriminant analysis of all four recommender systems

ANNEXURE-III



ANNEXURE-IV


Second Read (Collection)
0
1
2
3
4
5
6
7
8
Acedmia .edu
Google Scholar
Research Gate
Google Scholar
Google Scholar
Acedmia .edu
Google Scholar
Research Gate
Google Scholar
Research Gate
Google Scholar
Research Gate
Google Scholar
Mendeley
Acedmia .edu
Google Scholar
Research Gate
How much mental and perceptual activity was required? Was the task easy or demanding, simple or complex
How much time pressure did you feel due to the pace at which the tasks or task elements occurred? Was the pace slow or rapid?
How successful were you in performing the task? How satisfied were you with your performance?
How hard did you have to work (mentally and physically) to accomplish your level of performance?
How irritated, stressed, and annoyed versus content, relaxed, and complacent did you feel during the task?
The recommendations are Useful for me
The recommendations are surprising to me
The recommender provides an adequate way for me to express my preferences
The items recommend to me tool my personal context requirements into consideration
The system helps me understand why the items were recommended to me

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PUBLICATION VI

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