**Wee Kim Wee School of Communication and Information**

**CI6299 – Critical Inquiry**

**Proposal Submission**

**Research Topic**: Artificial Intelligence and Human Recommendations in Decision Making

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## 1. Aims of the Research:

This study aims to study investment decisions between AI-Recommender Systems (ARS) and Human-Recommender Systems (HRS) with regard to an individual's financial self-efficacy and technological self-efficacy. Financial self-efficacy focuses on the individual's stock investing experience while technological self-efficacy considers the individual's exposure to digital technologies. The study will look into these concepts as these might have bearing on the individual's reception of ARS versus HRS.

**Commented [#A1]:** Better to say "individuals" instead of "subjects"

**Commented [#A2]:** Do not use the word "investor" in the research objective statement since you may get all the participants as investors.

**Commented [ML3R2]:** Ok. We switched this to 'subject'

**Commented [ML4R2]:** This paragraph forms an introduction, we expounded on these two concepts in the background below.

## 2. Background to the Research

The advancement of technology in recent years and its ability to enhance the efficiencies of work had led to its proliferation in many facets of society today. In the area of financial services, financial technology (FinTech) is used to improve several financial activities such as virtual robo-advisors for stock investing. The amount of financial capital invested into the FinTech industry is projected to continue growing in the coming years: a study by Statista (2017) predicted the amount of assets-under-management by robo-advisors to exceed $1 trillion by 2021. Despite the large amount of capital invested, the greatest utility of AI resides in high-frequency trading as it involves complex statistical techniques that adequately exploits AI's capabilities relative to that of a human. On the other hand, AI's effectiveness as recommendation systems for investing – where the crux of analysis is focused on the ability to reason – still remains a challenge (Ray, 2018).

Studies on technological self-efficacy and how it leads to an individual's stock investment decisions with ARS are lacking. Rather, most research focuses on human's personalities and reactions when interacting with AI-agents such as chatbots, with results showing that human-to-human interactions tended to exhibit more receptive behaviours as compared with human-to-AI interactions (Fischer, Foth, Rohlfing & Wrede, 2011; Mou & Xu, 2017). These studies are still useful as these behaviours might suggest an aversion to ARS when investing. However, the dearth of research in this domain calls for a deeper look, since technological self-efficacy might affect the individual's trust in an ARS when investing.

Another factor that can inadvertently affect stock investment decision-making is human biases (Kengatharan, 2014). Literature surrounding these biases have been well-studied (Zahera & Bansal, 2017) with scholars noting its increased relevance in certain contexts i.e. penny-stock investors exhibit more pronounced herding effects[1] (Kumar & Goyal, 2014). The consequence of these biases

[1] Herding is largely a phenomenon where investors follow what they perceive other investors are doing, rather than their own analysis.

is that, investors' decision making could be distorted by social or cognitive factors. Nonetheless, there is a lack of study into behavioural biases when it comes to following recommendations from an AI-agent.

### 3. Problem Statement and Objectives

With increasing adoption of AI technologies in the area of stock investing, it is imperative to investigate how ARS affect the decision-making strategies of an investor. To this end, the specific objectives of this study are:

Commented [#A5]: Agent or recommender system? If you are using ARS and HRS, try to stick with these terms.

Commented [ML6R5]: ok

1. How financial self-efficacy affects an individual's decision to follow either an ARS or HRS.
2. How technological self-efficacy affects an individual's decision to follow either an ARS or HRS.
3. To understand whether an ARS or HRS would influence an investor's decision (buy or sell) in either a large capital vs a small capital stock. To explore the effects on an investor's decision to invest on a large capital vs small capital stock when recommended by an AI agent vs a human.

Commented [#A7]: Try to explicate these two concepts—financial self-efficacy, technological self-efficacy—very well.

### 3. Literature Review

**Technological self-efficacy** could influence the process of adopting a certain technology, since it represents the confidence in a person's ability to handle a 'complex' technological innovation. Evidence presented by Kulviwat, 2014 had shown significant correlation on the effect of self-efficacy on perceived usefulness and ease-of-use with regard to a high technological innovation. Following the Technology Acceptance Model (formulated by Davis et al, 1989), a technological innovation is accepted based on two beliefs: high perceived usefulness and ease-of-use. This is also congruent with other studies (Keng Siau et al, 2018; Xin Li et al, 2012) on 'technology trust' being measured by the technology's capability, reliability and performance (or the technology's usefulness).

An individual's **financial self-efficacy** could hold significance in an individual's financial behaviour (Farrell, Fry & Risse, 2016). It refers to "one's belief about their capability of organizing and executing courses of action to achieve one's ultimate financial goals" (Forbes & Kara, 2010). The role played by financial self-efficacy in various financial decisions had been well-studied by scholars, including that of financial satisfaction (Asebedo & Payne, 2018); financial inclusion (Mindra & Moya, 2017); and savings behaviour (Magendans et al., 2017).

In addition, the financial self-efficacy levels of an individual could cause them to adopt various experiential and rational thinking styles (Sagone & De Caroli, 2013); individuals with high self-efficacy levels exhibited higher levels of experiential and rational processing. In a study by Farrell et al. (2016) on 1542 Australian women, it was found that a woman's financial self-efficacy can exert a bearing on her financial outcomes. In particular, higher levels of financial self-efficacy was associated with more rational and responsible financial decisions (thus the possible reduction in human biases). It should be noted, however, that these studies looked at the individual's financial activities as a whole – encompassing a range of financial products such as investments, mortgages, loans, etc and were not applied solely in a stock investment context. This research gap thereby ~~and therefore~~ necessitates further inquiry into its relevance.

**4. Scope of the Research**

The study will be conducted over the course of one semester (January to May 2020), with a maximum of 150 participants. ~~We would select a sample of the target participants based on their interest in stock investing.~~Sampling techniques such as convenience sampling would be implemented to select the target participants based on their interest in stock investing.

The study is only concerned with the decision made to follow human or AI advice and does not concern itself with the type of investment platform or specific stocks. This is to ensure that the individual preferences or biases do not distort or skew the data collected in any way.

We would explore several constructs such as the technological self-efficacy and financial self-efficacy of the subjects for this study.

**5. Methodology**

The study would employ a questionnaire to collect the necessary data. The questionnaire would be distributed electronically to the subjects to gather data relating to the following:

- Subject's technological self-efficacy
- Subject's financial self-efficacy
- Screens depicting both HRS and ARS for either a large-cap or a small-cap stock, so as to capture the subject's decision on which stock to invest in

An analysis of the responses would then be done with statistical analysis methods and the findings would be discussed in the final report.

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**Commented [#A13]:** This is ok in the method section. But not ideal in the introduction section.

**6. Research Schedule**

| Week | Date | Milestone |
|---|---|---|
| Week 3 | 31 January, 2020 | Proposal Submission |
| Week 4 | 07 February, 2020 | Preparation of Questionnaire for Research Subjects |
| Week 5 | 14 February, 2020 | IRB Application (before Week 6 – 21 Feb 2020) |
| Week 8 | 06 March, 2020 | Report Draft |
| Week 9 | 13 March, 2020 | Deployment of Questionnaires |
| Week 12 | 27 March, 2020 | Integrate Results and Findings into Report |
| Week 13 | 27 April, 2020 | Final Report Submission |

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