## A Cross-Cultural Recommender System

### A Cross-Cultural Recommender System

Ву

Kathy Tian

Edited with a Foreword by Robert Tian

Cambridge Scholars Publishing



A Cross-Cultural Recommender System

By Kathy Tian

Edited with a Foreword by Robert Tian

This book first published 2026

Cambridge Scholars Publishing

Lady Stephenson Library, Newcastle upon Tyne, NE6 2PA, UK

British Library Cataloguing in Publication Data A catalogue record for this book is available from the British Library

Copyright © 2026 by Kathy Tian

All rights for this book reserved. No part of this book may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, recording or otherwise, without the prior permission of the copyright owner.

ISBN: 978-1-0364-6020-4

ISBN (Ebook): 978-1-0364-6021-1

#### To my mother and father, This book would not be possible without you.

### TABLE OF CONTENTS

Preface ix
Acknowledgmentxi
Foreword by Robert Tianxii
Chapter One1
Introduction
1.1 Recommender Systems and Cultural Influences
1.2 Purpose and Structure
1.3 Theoretical Orientation and Contribution
Chapter Two8
Cross-Cultural Issues and Machine Learning
2.1 Cross-Cultural Dimensions
2.2 Prior Research on Cross-Cultural Recommender System Use
2.3 Critiques of Hofstede
2.4 Machine Learning Recommend System
Chapter Three
Changes in China and Cross-Cultural Recommender System
3.1 Demographic Landscape Changes in China
3.2 Individualism in China's Younger Generation
3.3 Cross-Cultural User Interface and User Experience
Chapter Four
Recommender Systems and Design
4.1 Holistic versus Analytical Processing
4.2 Product Involvement as Moderator
4.3 Navigation Speed and Design Preferences
Chapter Five
Individualism vs. Collectivism
5.1 Difference within American Culture
5.2 Differences within Chinese Culture
5.3 Differences between American and Chinese Cultures

viii

Chapter Six	68
Analytical-Holistic Information Processing	
6.1 Difference within American Culture	
6.2 Differences within Chinese Culture	
6.3 Differences between American and Chinese Cultures	
Chapter Seven	99
Ecological Validity	
7.1 Between Cultures Differences of Individualism-Collectivism	
7.2 Between Cultures Differences of Analytical-Holistic	
Chapter EightConclusion	118
	100
References	128
Appendices	143
Index	158
About the Author	166

#### **PREFACE**

Recommendation engines have become a pervasive component of consumers' everyday lives. These recommender systems are employed on e-commerce sites across the world. However, despite their pervasive presence, the user interface design and the way products are recommended, these systems are relatively similar across cultures. Across three studies, I explored how culturally informed cues, both social and visual, affect preferences for a recommender system's style and design.

Specifically, I examined how values of individualism-collectivism and differences in information processing influence consumer behavior in the recommendation system from both within- and between-culture perspectives (e.g., individual-level and national culture). Consumers from collectivistic cultures (e.g., China) and those who exhibit more collectivistic qualities at the individual level are believed to prioritize the needs of the in-group over individual preferences compared to their individualistic counterparts.

Collectivists are more concerned with peer perceptions and are more susceptible to social influence on social networking sites than individualists. Participants were exposed to two recommender system design conditions to understand whether these values would affect consumers in the context of e-commerce recommender systems. They viewed products that were either recommended by a socially similar character or by a generic recommendation engine.

Similarly, East Asian individuals are believed to attend to and process information holistically and incorporate more information relative to Westerners. These differences in processing styles stem from tendencies toward holistic or analytical information processing. Holistic processing involves attaching relationships between objects, while analytical processing focuses categorically on focal objects.

Participants viewed either a recommender with high or low information density to investigate how information processing influences consumers within and between cultures. The studies showed no interaction effects between the level of individualism-collectivism, information processing, or national culture and condition. Individuals scoring higher for collectivism, particularly Chinese (vs. American) participants, did not prefer a recommendation system where a socially similar character recommended the products. Likewise, Chinese (vs. American) participants and those

x Preface

scoring higher for holistic tendencies did not prefer a more informationdense recommender. These findings were consistent using self-reported responses and when behaviours were tested on a website shopping platform.

The three-part studies suggest cultural information cues may not be as salient in online settings. Additionally, Chinese and American participants did not consistently differ in their level of individualism, which may be a function of China's socio-economic landscape. This research contributes to the ongoing debate about whether Hofstede's cultural dimensions and differences are stable. It also addresses questions of how new technologies influence culture and behaviours.

#### **ACKNOWLEDGMENTS**

Firstly, I want to thank my parents for all they have worked to give me a better future. They have been a source of support, motivation, and encouragement throughout my academic career and beyond. I am incredibly grateful for the time, patience, and guidance they have devoted to me. As I reflect upon the blessed life I have lived and the education I've received, I want to thank my parents for making these opportunities possible through their dedication.

To my doctoral advisor, Dr. Mike Yao, you have contributed significantly to my development these past years. Our conversations have been profound and have affected the way I perceive myself. Thank you for believing in my abilities when I struggled to see them myself. You have not only helped me to discover my intellectual and personal interests but also taken the time to guide me toward a more authentic path. Thank you for contributing to my self-discovery and encouraging me to actualize my aspirations. Without you, I would not be on my professional course today.

To my mentor, Michelle, I appreciate all the careful attention you put into your work as an advisor and researcher. You genuinely care about your students, going above and beyond what is expected to help them succeed. I have been fortunate to work with you on various projects throughout my studies. Your dedication to the quality of your work and relationships with students was always apparent to me. As a mentor, you are patient, considerate, and work with integrity. Thank you for teaching by example. I have learned much from you and will continue to do so.

To Professors Michelle Nelson, Chang-Dae Ham, and Russell Belk, your wisdom, compassion, and guidance have been invaluable to me. This book would be impossible without your combined knowledge and interdisciplinary expertise. Thank you all for providing me with feedback and helping me to cultivate my interests over these years. I have enjoyed your thoughtful and eye-opening conversations, and you have contributed significantly to how I approach my research today. I feel blessed to have such an outstanding group of advisors. Thank you.

#### **FOREWORD**

#### ROBERT TIAN

The scent of jasmine tea lingers in the air as I settle at my desk, the same wooden surface where my daughter, Kathy, once sprawled with coloring books, her pigtails brushing the edges of crayon-strewn papers. Now, years later, the desk holds stacks of her doctoral research—manuscripts marked with her precise annotations, copies of *Journal of Consumer Research* dog-eared at pages discussing recommender systems, and a framed photo of us from 2008: a sunlit day in Beijing, her teenage self-squinting at the camera while clutching a volunteer badge for the pre-Olympic games. As I trace the outline of her handwriting in the margins of a draft, I am struck by the profound alchemy of time—how those tiny hands that once tugged at my sleeve to "lift her higher" now wield theories that bridge continents and cultures.

#### The Seedlings of Curiosity: Identity in Miniature

Kathy's earliest inquiries into selfhood emerged not in academic journals but in the tender struggles of childhood. I recall a crisp autumn afternoon when she returned from school, her backpack slung over one shoulder, her voice trembling with a mix of frustration and confusion: "Baba, why do Jessica and Lucy wear their hair the same way I do? Why do they copy everything I say?" I knelt to meet her gaze, brushing a leaf from her windtossed hair, and saw in her downturned eyes a flicker of the existential question that would later define her scholarship: *How does one retain individuality in a world that seeks to mirror or mold?* 

"You know, my little star," I said, tucking a stray curl behind her ear, "fireflies don't dim their light because others seek to gather near it. They shine brighter, because that's how they teach the world to find beauty in uniqueness." She didn't fully grasp it then, but that moment—like so many others—planted a seed. Years later, as she delved into the cultural dynamics of recommender systems, I recognized the same tension at the core of her work: the interplay between individual preference and

collective influence, and between algorithmic homogenization and the human need for authentic identity.

Her childhood was a patchwork of dualities—growing up in Buffalo, New York, with weekends spent practicing calligraphy and reciting Tang poems, balancing American Girl dolls with visits to her grandparents' courtyard in Beijing. This liminal existence, suspended between two cultures, became her intellectual playground. At 12, she wrote a journal entry titled "My Two Mirrors," in which she wondered: *Does the me in English class see the world differently than the me in Chinese school?* Little did she know that this question would evolve into a doctoral thesis exploring how national culture shapes trust in machine-driven recommendations. This query straddles the realms of consumer behavior, information science, and cross-cultural psychology.

#### The Crossroads of Heritage and Horizon: A Journey in Two Cultures

Our return to China in 2011 was not just relocation but a reckoning with heritage. Kathy, then 17, faced a paradox familiar to third-culture kids: fluent in Mandarin but unversed in the subtleties of Chinese social norms, connected to her ancestry yet shaped by Western education. At Beijing Foreign Studies University (BFSU), I watched her navigate this divide with the tenacity of a cartographer mapping uncharted terrain.

Our kitchen-table debates became crucibles of ideas. Over steaming bowls of hand-pulled noodles, Kathy would challenge me on the cultural biases embedded in marketing theories: "Baba, if Hofstede's individualism-collectivism dimension is rooted in Western scholarship, how does it apply to China's youth, who grew up with social media and globalized markets?" Her questions were not merely academic; they were deeply personal, a quest to reconcile her dual identities. When we co-authored a paper on cross-cultural advertising, I saw her meticulousness firsthand—how she pored over studies on guanxi (social networks) and guochang (national pride), insisting on nuance over generalization. "We can't treat cultures as monoliths," she'd say, tapping a highlighter on a graph showing generational shifts in China's individualism scores. "Especially not when technology is rewriting the rules of connection."

Yet her hunger for independence soon emerged. One evening, as we revised a draft, she pushed the manuscript aside gently. "Baba," she said, her voice steady, "I need to build my own arguments now. Not just echo yours." I felt a pang of pride, of loss, of awe—as I realized she was no longer a student absorbing knowledge but a scholar demanding to be heard

xiv Foreword

on her own terms. That night, I wrote in my journal: To raise a thinker is to learn that your greatest legacy is not what you teach them, but what they teach you about letting go.

## The Alchemy of Academic Rigor: From Hypothesis to Humanity

Kathy's doctoral work at the University of Illinois Urbana-Champaign was a testament to this resolve. She chose a topic at the nexus of technology's ubiquity and humanity's complexity: *How do cultural values shape consumer interactions with recommender systems?* On the surface, it was a study of algorithms and user interfaces; at its core, it was an exploration of how culture encodes trust, identity, and choice in the digital age. Her research design was elegant in its ambition. Three interlocking studies:

- 1. **The Social vs. Algorithmic Divide**: Comparing how U.S. and Chinese consumers responded to recommendations from peers versus machines, rooted in theories of holistic (Chinese) vs. analytical (Western) thinking.
- 2. **Information Density and Cultural Cognition**: Testing whether high-detail interfaces resonated more with analytical minds, while holistic thinkers preferred contextual cues—a hypothesis inspired by Nisbett's cross-cultural cognition research.
- 3. **The Ecology of Digital Behavior**: Building a mock shopping website to collect real-time interaction data, bridging lab experiments with real-world validity.

I remember the night she called from her campus lab, her voice buzzing with excitement: "Baba, the pilot data shows something incredible. Chinese participants spend 30% more time examining the *context* of recommendations—like who else bought the product—while Americans focus on individual ratings. It's exactly what the holistic-analytical framework predicts!" Her enthusiasm was contagious, but what struck me most was her commitment to grounding theory in human experience. She didn't just analyze algorithms; she interviewed users, asking: *How does this recommendation make you feel? Seen? Manipulated?* 

This humanistic lens defined her work. When she approached Dr. Russell Belk, a luminary in consumer culture theory, to join her dissertation committee, she didn't just cite his work—she articulated how his theories on materialism and self-identity could deepen her analysis of China's "iGen" cohort. "I want to understand how digital natives, raised in China's

era of rapid modernization, negotiate between collectivist roots and individualistic aspirations through algorithmic interactions," she told him. Dr. Belk later told me, "Kathy's work is a rare blend of rigor and heart. She doesn't just study technology; she studies how technology *feels* to the people who live with it."

#### The Language of Love in Academic Latitudes

Witnessing Kathy defend her dissertation was a surreal convergence of past and present. On a Zoom call in April 2020, I watched her navigate a gauntlet of questions from professors, her poise belying the tremble in her voice when she concluded: "This research is a love letter to the complexity of human choice—how culture, technology, and identity dance in the digital marketplace." When the committee chair announced her approval, she turned to the camera, her eyes bright: "Baba, did you hear? I'm Dr. Tian."

I thought of the little girl who once feared being overshadowed, now standing in the fullness of her own intellect. Her career choices—joining IBM as a cross-cultural marketing engineer, relocating to Europe for family during the pandemic—reflected a wisdom that transcended academia. She had learned, as any true scholar does, that knowledge is only valuable insofar as it serves people. When she explained her decision to prioritize industry over academia, she said, "I want to see these theories in action, Baba. To help companies design systems that respect cultural nuance, not just exploit data."

This book is that vision made manifest. It is a scholarly treatise on recommender systems, yes—but it is also a memoir of identity, a father's testament to a daughter's journey from "lifting higher" to helping the world see higher. In its pages, you will find rigorous analyses of IND-COL theory and machine learning. Still, you will also encounter the heartbeat of its author: a third-culture thinker who understands that algorithms, like humans, are shaped by the cultures they serve.

As I close this foreword, I glance again at the photo from Beijing. The girl in it could not have known the path ahead—the dissertations, the defenses, the titles. But in her squinting gaze, there was a determination that only children of migrants possess: the resolve to belong nowhere and everywhere, to weave multiple worlds into a single, coherent truth. Kathy's work is a celebration of that resolve—a reminder that the most profound academic contributions are often born from the most personal questions.

xvi Foreword

To my daughter, the once-little girl who now lifts others with her mind: May this book be a bridge, connecting cultures, disciplines, and the quiet moments of childhood curiosity to the grand tapestry of human knowledge. You have always been my "little star." Now, let your light guide others to see the world as you do—complex, beautiful, and endlessly worth understanding.

#### CHAPTER ONE

#### INTRODUCTION

After a long workday, you get home and open Spotify's "Discover Weekly" to jam to your favourite tunes. Of course, you did not select songs yourself; Spotify's algorithm found top hits matching your preferences. Instead of unwinding with your favourite playlist, perhaps you choose to watch a sitcom. You open your Netflix or Youku account and do not need to search for long before stumbling upon a comedy you like.

Based on your past selection of movies and television programs, Netflix identifies your preferences and recommends that you watch "The Office" today. Before the night ends, you decide to do some online shopping. As you open Amazon or Alibaba, you are bombarded with a front-and-centre row of recommended products "based on your past purchases."

The truth is incontrovertible: recommender systems (RS)<sup>1</sup> are now pervasive in contemporary retail and everyday consumer life. Machine learning RS (e.g., "based on past purchases" on Amazon) has ingrained itself into the consumption network, securing its position as an indispensable spoke in the wheel of consumerism. These recommender algorithms have lured consumers with the conveniences they provide, and this dependence has unintended side effects. Increased product consumption for companies is being achieved by implementing these systems.

#### 1.1 Recommender System and Cultural Influences

Despite their blockbuster debuts and subsequent dominance in early American tech, behemoths like Pandora and Netflix have received relatively little attention from consumer behavior research. Conversely, the

<sup>&</sup>lt;sup>1</sup> RS is shorthand for recommender system and is used interchangeably with other terms (e.g., recommendation algorithm, recommender engine) like in Lee & Hosanagar (2014).

consumer perspective has not been a focal point of research in information science or user design (UI)/user experience (UX). As such, I hope to address the gaps in these fields by exploring how national culture influences (1) UI/UX preferences and trust on recommender sites, (2) consumer purchase intentions and trust, and adjective perceptions on RS, and (3) whether a machine learning algorithm can accurately predict differences in cultural use of RS.

As Silicon Valley's emphasis on technology has come to characterize today's business spirit, algorithms are becoming a critical component of success. Researching how consumers engage with new technologies is ever more pressing. Although there exists literature following developments in social media (e.g., see Lipsman et al., 2012; Whiting & Williams, 2013), electronic word-of-mouth (e.g., see Chu & Kim, 2011; Lee & Youn, 2009), and the Internet of things (e.g., Ko et al., 2005) as they pertain to consumer behavior effects, it appears as though recommendation systems have been relatively overlooked.

As the use of recommenders in business has become commonplace, the importance of understanding their use more deeply is evident. Today, the application of RS is prevalent in the United States and China. According to a 2018 SEC filing, China's Alibaba reported 617 million mobile users per month and boasted 552 million active users on retail marketplaces, such as Tmall and Taobao.

Moreover, JD.com, another e-commerce site in China, had 292 million customers during the same period (Laubscher, 2018). For companies in the United States, Amazon has roughly 300 million active users (Smith, 2019), and Netflix is approaching 150 million users (Fiegerman, 2019). Beyond these notable brands, there is an abundance of companies employing recommenders in the United States (e.g., Coursera, Google, Walmart, Target, Sam's Club, Audible, Meijer, Best Buy, YouTube, Etsy, and eBay, to name a few) and China (e.g., Baidu, Ali Express, M18, Dang Dang, Mini In The Box, Deal Extreme, and Vancal, to name a few).

To address the previously mentioned gap, I aimed to study how national culture affects interactions with recommenders in China and the United States. A wealth of literature has focused on culture's influence on consumer behavior (e.g., Peter et al., 1999), reception and presentation of advertising (e.g., Liu et al., 2009; Nelson & Paek, 2005; Whitelock & Chung, 1989), and identity (e.g., Belk & Wallendorf, 2012) as relating to both online and offline behavioural intent. By contrast, interest in the use of recommendation engines across countries has been relatively lacking in consumer behavior research.

Introduction 3

A few studies in the fields of information science, UI/UX, and computer science have investigated differences in cross-cultural use of RS, yet the proportion of studies is not significant, and very few have interrogated the question from a consumer behavior perspective (e.g., see Berkovsky et al., 2018; Chen & Pu, 2008, 2014; Li & Guo, 2018). Although RS implementation originated in the United States, a highly individualistic country (Shavitt et al., 2011), the rollout of music streaming companies and video browsing platforms led to their application (i.e., their implementation in different countries) crossing international borders long ago (Time, 2010).

When it comes to physically tangible products, such as McDonald's meals, or overtly visible products, like Facebook or RenRen, there has been systematic research on how these products are used, received, or altered across cultures. Studies, for instance, have explored the localization of international fast-food chains (e.g., Watson, 2006; Yeu et al., 2012) and the different uses and gratifications for culturally-specific social media applications (e.g., Qiu et al., 2013). Yet, few studies have investigated how recommendation engines are modified to international markets or how national culture informs consumer behavior within these systems.

Culture has been found to inform cognition, such that East Asians tend to perceive information holistically, whereas Westerners process information analytically (Ji & Yap, 2016; Nisbett et al., 2001). Differences in social norms across cultures encourage different cognitive processing patterns, with individuals from Eastern and Western cultures exhibiting remarkably divergent processes (Boduroglu et al., 2009; Monga & Williams, 2016). Specifically, people in Eastern cultures generally value social relations over individual needs, focusing on broader contexts (Monga & Williams, 2016; Nisbett & Miyamoto, 2005).

This tendency refers to holistic processing, which involves orientation to areas or contexts and is prevalent among Easterners, as shown by eye-tracking studies (Chua et al., 2005; Monga & John, 2006). Conversely, Westerners emphasize social relations to a lesser degree, encouraging individuals to perceive reality as discrete and focus chiefly on object attributes (Monga & Williams, 2016; Williams et al., 1998). This cognitive heuristic, known as analytical processing, involves detaching focal objects from context and tends to assign objects to categories based on attributes (Nisbett et al., 2001).

Considering extant evidence suggesting visual perceptual stimuli are processed distinctly contingent on cultural tendencies, it has been recommended that the fundamental ways in which Easterners and Westerners engage with shopping decisions, both online and offline, differ in culturally

relevant ways (e.g., see Bao et al., 2003; Ji & Yap, 2016; Li et al., 2018; Monga & Williams, 2016). For instance, Becerra et al. (2013), using respondents from the United States and South Korea to represent analytically- and holistic-thinking cultures, respectively, found that reliance on trust is more pronounced for holistic shoppers.

Further, studies suggest that Easterners are more comfortable with higher content quantity than Westerners and prefer to observe objects in relation to their context (de Oliveira & Nisbett, 2017; Miyamoto et al., 2006; O'Donovan et al., 2016). For example, O'Donovan et al. (2016), using language to represent holistically and analytic thinking, found that Korean and Japanese speakers consistently selected more complex user interface (UI) designs than English-speaking participants.

As such, it is possible that variations in cognitive processing styles could lead to different preferences for an RS's user interface. Specifically, holistic thinkers may exhibit a greater inclination for online browsing or price comparison behaviors compared to their analytical counterparts, who may prefer seeing fewer items and feel less inclined to compare items across various attributes (e.g., see Dong & Lee, 2008; Epstein & Pacini, 2001).

Regarding recommendations, it has been suggested that differences in individualism and collectivism significantly predict social influence on mobile phone RS, with East Asian collectivists being more affected than those from the United Kingdom (Choi et al., 2014). In addition, differences in cultural dimensions (Hofstede, 2001), such as tendencies toward prioritization of social harmony versus self-actualization (i.e., individualism versus collectivism), have been found to relate to crosscultural RS use, online influence, and design preferences (Berkovsky et al., 2018; Chen & Pu, 2008, 2014).

Prior studies, for instance, suggest Chinese consumers may be more impressionable to online influence, consider the suggestions of others more heavily than Westerners, and are more prone to conformity (Chu & Choi, 2011; Huang & Harris, 1973; Imada, 2012; Kim & Markus, 1999; Ng, 2003). Essentially, variations in individualistic and collectivistic cultures (IND-COL) refer to how people focus on reliance or independence. It is believed that there is a greater emphasis on independence (Individualism) in Western cultures.

At the same time, in-group connectedness is emphasized in East Asian cultures, which are often considered collectivistic (Singelis, 1994, 1995). Given the variation in emphasis and research on cross-cultural RS use in social influence, I am interested in understanding how Chinese and American participants differently assess their purchase intentions, perceptions

Introduction 5

of the design's adjectives, and trust in the recommender, depending on whether a socially similar character suggests the product.

#### 1.2 Purpose and Structure

In this book, I intend to investigate whether Chinese and American consumers interact differently with recommendation engines. China and the United States were selected for this research as they represent the world's largest (15.9% share of total e-commerce retail sales) and second-largest (7.5% share of total e-commerce retail sales) e-commerce markets, respectively (Edquid, 2017).

As most e-commerce sites implement some RS, the e-commerce sales market corresponds highly to RS engagement (Schafer et al., 1999). Based on prior work and the wide adoption of RS, I examined how differences in IND-COL and information processing influence RS use in a country tending toward holistic processing (China) and a country tending toward analytical thinking (United States) (Masuda & Nisbett, 2006; Monga & John, 2006; Nisbett & Miyamoto, 2005).

Additionally, this book explores variations in culture within China. The younger generation of Chinese consumers, known as "late-Millennials," born in the 1990s, and "iGen," born after 1995 or in the early 2000s (Center for Generational Kinetics, 2019), was raised during a time when China was increasingly exerting its socio-economic influence (Shambaugh, 2013), it would be valuable to consider how age affects IND-COL tendencies in contemporary China.

I propose a three-part study to explore the influence of national culture on RS engagement: (1) in studies 1A-1C, I evaluate how U.S. and Chinese consumers responded to a conventional recommender versus one displaying peer ratings, from both a within and between-cultures perspective, (2) studies 2A-2C measures whether there are differences in how U.S. and Chinese consumers engage with a high or low information density RS, both within and between cultures; (3) finally, to explore the ecological validity of the experiments, I built a website for studies 3A-3B to collect behavioral data of how American and Chinese RS users interact with different designs. As relatively few consumer behavior and advertising papers have been dedicated to researching cross-cultural RS use, this research addresses a knowledge gap in these fields.

Further, since few consumer behavior researchers have experimentally studied cross-cultural recommender use, this book enhances the understanding of recommenders and their relationship to consumer behavior. Additionally, this three-part study contributes to the extant literature in information science and UI/UX by analyzing questions of cross-cultural RS use from a consumer perspective. As late-millennial (born ≥ 1990) and iGen (born ≥ 1995) Chinese consumers, they have been exhibiting shifting tendencies toward individualism (Ngai & Cho, 2012; Moore, 2005; Yi, 2018). This research adds to current knowledge by exploring within-culture differences toward RS engagement. Finally, this book humbly contributes to information science research in developing and testing a novel workflow.

#### 1.3 Theoretical Orientation and Contribution

Although RS is used across countries and cultures, the basic design of various RS is similar worldwide, particularly in terms of the underlying algorithm approaches and user interface design (Bakaev & Avdeenko, 2012; Sarwar et al., 2001). Many e-commerce sites employing recommenders apply a similar user-facing design template (i.e., squares containing images of the items along a row; see Appendix), regardless of whether the RS is used in China (e.g., Alibaba, JD.com) or the United States (e.g., Amazon, eBay), all follow comparable design guidelines (Bakaev & Avdeenko, 2012), with relatively few modifications to the interface design.

One purpose of this study is to suggest whether and how to optimize the user interfaces of RS across different countries. Additionally, recommendations are made for whether the algorithms require adjustment based on the findings of this three-part study. New research on interface design and algorithm tuning could significantly impact the effectiveness of RS operated by international companies.

Further, this research applied IND-COL theories and analytical versus holistic information processing to a new context: the cross-cultural understanding of recommendation system use. Although the values of IND-COL have indeed been successfully examined online or in other media (e.g., social networking sites, electronic word of mouth) and in brick-and-mortar consumer retail (Chu & Kim, 2011; Chung & Drake, 2006; Lee & Youn, 2009; Lipsman et al., 2012), to the best of my knowledge, these studies did not examine machine-based suggestions against human suggestions. The widespread adoption of RS in their modern forms is relatively recent, and the prevalence of machine-based recommendations is a new phenomenon.

As such, this research aimed to contribute to the theory and development of IND-COL by applying it to a recent phenomenon using an experimental design approach. This work, with its significant positive effect, would contribute to a better understanding of how IND-COL shapes engagement with RS, a relatively new technology. Conversely,

Introduction 7

suppose no significant difference is found between how Chinese and American consumers interact with recommenders. In that case, this will allow the stability of this dimension to be called into question (as applied to machine-based recommenders).

This three-part study contributes to the extant theory on IND-COL by quantitatively exploring the within-cultural differences in China. This (born  $\geq$  1995) differs from prior generations in expressions of IND-COL. As such, this research adds to the ongoing conversation about the validity of Hofstede's cultural dimensions over time (Dimitrov, 2014; Holt,1994; McSweeny, 2002; Yi, 2018).

As Hofstede's dimensions assume culture is static across time and fail to account for culture's ever-evolving nature, this study contributes to the theory by questioning the application of IND-COL in modern China. The case of China is imposing, given the country's rapid rise to wealth beginning in the late 1990s and early 2000s (World Bank, 2019), largely coinciding with the birth of the iGen generation (Center for Generational Kinetics, 2019), as it represents an evident example of how societies progress given time. Overall, by examining the generational and within-cultural differences of IND-COL, I joined the conversation on whether and how Hofstede's dimensions, which assume cultural values are fixed, should be applied in a world where only constant changes occur (Oyserman et al., 2002; Oyserman, 2006).

Further, I contribute to the theory of analytical-holistic information processing by extending its application to a new context (i.e., cross-cultural use of RS). Although studies have applied this theory to discovering differences in web design across cultures (e.g., Faiola & Matei, 2005; Marcus & Gould, 2000; Liljenberg et al., 2019), few have examined its application to cross-cultural recommendation system use. Additionally, understanding how differences in analytical-holistic information processing affect consumers' design preferences on recommender sites is significantly valuable. International companies can leverage this knowledge to provide users with a better user experience (UX) and offer more intuitive recommendations.

Thirdly, this research can help to advance theoretical knowledge on steps to improve the accuracy of recommenders across cultures. Finally, this book contributes to the conceptual understanding of IND-COL and holistic analytical processing by using a mock shopping website to examine the ecological validity of the findings. If culture cannot be accurately predicted by how consumers behave on recommender sites, it raises the question of how these theories should be applied in non-laboratory settings.

#### CHAPTER TWO

# CROSS-CULTURAL ISSUES AND MACHINE LEARNING

#### 2.1 Cross-Cultural Dimensions

A combination of factors before the turn of the century, such as globalization and new information technologies, facilitated an onslaught of research on cross-cultural business, advertising, and management (Shavitt et al., 2011). Perhaps the most widely applied of these are Hofstede's (1980) four cross-cultural dimensions based on IBM surveys across 40 countries (Dimitrov, 2014; McSweeney, 2002). From his research, Hofstede asserts that culture is "software" and the "collective programming" of the mind, distinguishing one group of people from another along four (now six) work-related cultural dimensions (Hofstede 1980, 2001).

These original dimensions include (i) power distance (PDI), which reflects the degree to which unequal power distributions are accepted in society; (ii) individualism and collectivism (IND-COL), or the degree to which society emphasizes the role of the individual versus prioritizing group harmony; (iii) masculinity (MAS), referring to the degree which societies value traditionally masculine characteristics (e.g., ambition, achievement, and competition) compared to feminine characteristics (e.g., nurture and support); and finally, (iv) uncertainty avoidance (UAI), or the extent to which uncertain situations and ambiguity cause people to feel threatened (Hofstede, 1980, 2001; McSweeney, 2002; Yoon, 2009).

In later years, Hofstede included a fifth dimension, long-term orientation, which measures the propensity to be future-oriented versus immediately oriented. However, considering the difficulty of operationalizing this dimension and the suggestions that LTO fails to capture Eastern values accurately (Fang, 2003), long-term orientation lacks replication rigor (Fiske, 2002; McSweeney, 2002). More recently, a new dimension, indulgence versus restraint, which describes a culture's propensity to enjoy gratification freely or to suppress gratification, was also included (Hofstede,

2011). Once again, due to the lack of studies employing this measure, it will not be implemented in this study.

Of these four distinctions, I primarily examine IND-COL, given that this measure is the most broadly implemented of Hofstede's dimensions (Aaker & Maheswaran, 1997; Han & Shavitt, 1994), and its implications are immediately relevant to this study. The IND-COL distinction differentiates cultures based on dichotomous prioritizations of the self versus the group in society. People from individualistic cultures (e.g., the United States, Germany, France) are defined as "I"-conscious and exhibit concern for themselves or immediate in-groups above the collective (De Mooij & Hofstede, 2011; Hofstede, 2001).

In individualistic cultures, identity is perceived as dispositional and "in" the person. As such, personal freedom and autonomy are expected and prioritized in individualistic cultures (Cheng et al., 2018). Collectivism, conversely, is characterized by the responsibility to the family and emphasis on social harmony over personal goals (Cheng et al., 2018; Soares et al., 2007). People in collectivist cultures are considered "we"-conscious, loyal, and duty-bound (De Mooij & Hofstede, 2011; Gardner, Gabriel, & Lee, 1999). Their identities hinge on the more significant social system, preservation of respect (or "face"), and maintenance of social harmony (Hofstede, 2001).

The emphasis on in-group connectedness in collectivist societies affects behavior in both online and offline settings (Singelis, 1994, 1995). Further, past studies reveal how to focus on self-reliance/independence in individualistic societies. As collectivists stress group needs above individual ambitions, they are less willing to "stick out" and, historically, demonstrate lower needs for uniqueness and self-actualization compared to individualistic counterparts (Bian & Forsythe, 2012; Burns & Brady, 1992; Markus & Kitayama, 2012). Given these different value attributions, Chu and Choi (2011) find that Chinese internet users are more susceptible to social influence and likely to conform to peers' opinions. In contrast, their American counterparts use social networks to foster status and express uniqueness.

For example, Chu and Choi measured both the reliance and involvement of American (N=363) and Chinese (N=300) undergraduates with social media. The authors found social influence was more substantial for Chinese participants than American counterparts in opinion-seeking ( $\beta$ =.33, t=8.57, p < .001) and passing-along information ( $\beta$ =.22, t=6.25, p < .001). Considering these past findings, similar social influence behaviors should manifest in using RS manipulation to incorporate the ratings of socially similar peers on products.

In this study, I explore how cultural variation influences differences in how in-group social influence affects Chinese and American users in recommendation use. However, it is also important to note that what constitutes conformity and in what situations people may choose to express their uniqueness can be culturally relative. For instance, Belk (forthcoming) finds that there are local codes and nuances to luxury consumption in Japan. Cultures are intricate, and each larger group has variations within (e.g., subcultures). As such, more on within-cultural differences will be discussed later in this proposal.

Despite its widespread application, the IND-COL dimension has seen necessary additions and modifications over the past decades (e.g., Singelis et al.,1995; Triandis, 1982, 1995, 2001, 2018). Scholars have included the framework of horizontal-vertical IND-COL, with differences in horizontal and vertical values reflecting the degrees to which individuals within a given society accept high power distances or inequality (Nelson & Shavitt, 2002; Shavitt & Cho, 2016). Research on IND-COL generally contrasts differences across collectivistic or individualistic cultures but fails to account for intercultural variation (Zhang & Nelson, 2016).

Researchers observed that there were salient variations within individualistic and collectivistic cultures in sentiments toward social inequalities, distribution of wealth, and individual rank. Vertical cultures accept greater distances, whereas horizontal cultures seek to minimize social gaps (Shavitt et al., 2011; Triandis, 1995, 2018). Thus, the horizontal-vertical distinction of IND-COL creates a more detailed understanding of cultural differences relative to the broad and universalistic approach of Hofstede (1980, 2001).

In addressing perceptions of hierarchy in cross-cultural research, the horizontal-vertical distinction has been applied to traditional individualism-collectivism research, yielding more nuanced cultural groupings (i.e., vertical-individualism (VI), horizontal-individualism (HI), vertical-collectivism (VC), and horizontal-collectivism (HC). The VI cultures typically reflect societies such as the United States, Great Britain, or France, where individualism is prioritized, but hierarchy is prevalent. Conversely, horizontal individualists, generally reflecting cultures such as Denmark, Australia, and Sweden, emphasize self-direction but prefer more egalitarian social frameworks (Nelson & Shavitt, 2002; Shavitt & Cho, 2016).

Conversely, horizontal collectivism is reflected mainly in Latin American cultures, where equality and interdependence are essential (Torelli & Shavitt, 2010). Finally, vertical collectivists include societies such as China, Japan, and India, where collective harmony and social

status are valued. The addition of horizontal and vertical values to Hofstede's individualism-collectivism dimension has yielded more nuanced insights regarding consumer behavior in cross-cultural studies. Therefore, considering the previous findings suggesting that American culture tends to reflect individualism, whereas Chinese culture is associated with collectivism (Hofstede 1980, 2001; Triandis, 1995), I proposed the following hypothesis:

H1: American participants will report higher levels of individualism relative to their Chinese counterparts

### 2.2 Prior Research on Cross-Cultural Recommender Systems

Although no significant body of literature explores how culture influences interactions with RS, some studies in user interaction and information science have investigated this question. Berkovsky et al. (2018), for example, examined how culture affects trust in RS across four countries: Japan (N=110), France (N=112), Russia (N=123), and the United States (N=117). The researchers found that Hofstede's masculinity-femininity dimension significantly affected participants' preference of presentation style for recommended products (r=0.989, t (2)=9.58, p=0.01).

Japanese respondents were significantly more likely (p < 0.001) to trust the competence of a human representative's recommendation, whereas Russian respondents were less likely (p=0.009) to do so (Berkovsky et al., 2018). The authors suggest that Japanese participants were more inclined to trust the competency of a human-represented recommendation, as high MAS cultures, such as Japan, derive trust from inferred capabilities (Berkovsky et al., 2018; Doney et al.,1998).

In a similar study, Chen and Pu (2008, 2014) evaluated how Chinese participants (N=60) and Westerners (Swiss, French, German, and Italian; N=60) would interact differently with an organized recommender (i.e., products are organized into specific groups) compared to the traditional list view recommender. While both groups found that organized recommenders improved ease of use and usefulness, the effect was more substantial for Chinese participants (Chen & Pu, 2008, 2014).

Other research by Choi et al. (2014) found that IND-COL significantly predicts and moderates attitudes toward social influence on mobile phone RS. Specifically, the authors, using participants from Korea (N=310), China (N=105), and the United Kingdom (N=104) and using the country as a proxy measure for cultural identification, found the positive effect of

social influence on attitudes to be more assertive in collectivist (versus individualistic) users for mobile phone RS. Moreover, they found that the positive impact of recommendation quality on attitudes was more substantial in participants with higher technology UAI compared to those with lower technology UAI (Choi et al., 2014).

Further, studies have concluded that the strength of a social tie (i.e., how strong a social relationship is) affects the perceived credibility of a recommendation in a social RS (Oechslein & Hess, 2014). With participants from Germany (N=193), Oechslein and Hess (2014) found that when social ties were strong between the individual receiving the recommendation and the person making the recommendation, the suggestions were seen as significantly more credible than recommendations made from weaker social ties (p < .01).

Considering previous work in cross-cultural consumer behavior and interaction design, which suggests that Chinese consumers generally display more collectivistic tendencies than Westerners, the effect of socialtie strength on the perceived value of a recommendation may be even more pronounced. Recently, Li and Guo (2018) built a cultural distance-aware recommender algorithm based on Hofstede's cultural dimensions, operationalized at the country level, and demonstrated that the RMSE for their algorithm was, on average, 22.2%, 7.5%, and 13.4% lower than the service-based collaborative filtering, user-based collaborative filtering, and traditional hybrid collaborative filtering recommendation approaches. The increase in their prediction accuracy suggests that recommenders who account for cultural variation will likely outperform those who do not.

The majority of research focused on studying the cross-cultural use of RS has operationalized Hofstede's dimensions as national culture or at the country level (e.g., Berkovsky et al., 2018; Chen & Pu, 2008, 2014; Choi et al., 2014; Li & Guo, 2018), and the current approach to inferring a user's nationality through advertising cookies is also through the country, a similar approach will be taken in this proposal (Luna et al., 2002).

Additionally, Hofstede's dimensions have "been most widely adopted in cultural research in information technologies" (Choi et al., 2014, pg. 68) and "[Hofstede's] broad cultural construct has been thoroughly empirically tested [in information science] and thus would appear ripe for application to cross-cultural usability models" (Barón et al., 2009, pg. 2), it may be a suitable approach focused on the current study 2, focused on UI/UX, information science, and consumer behavior.

<sup>&</sup>lt;sup>2</sup> It is important to note that culture is a complicated and intricate concept. The significant work in this area comes from sociology and anthropology, in which culture is considered at a deeper level. As most of the cross-cultural research in RS

As the studies reviewed here on the cross-cultural use of RS in information science and UI/UX have given relatively little focus to the consumer behavior perspective, I hope to contribute to understanding how national culture is related to consumer preferences. Additionally, consumer research has yet to significantly explore the effects of national culture on RS use; this research will help shed light on how people engage with recommenders.

I believe that information science and UI/UX research would be interesting. Thus, based on previous research, I predicted the following hypotheses regarding the effects of cultural dimensions on RS use:

H2a: There is an interaction between recommender type and individualism, such that a content-based recommender will be more effective in increasing a) purchase intention, b) trust, and c) perception toward the products than a socially based recommender among Chinese consumers with high levels of individualism than those with low levels

H2b: There is an interaction between recommender type and individualism, such that a content-based recommender will be more effective in increasing a) purchase intention, b) trust and c) perception toward the products than a socially based recommender among Chinese consumers with high levels of individualism than those with low levels

H2c: There is an interaction between recommender type and national culture, such that a content-based recommender will be more effective in increasing a) purchase intention, b) trust, and c) perception toward the products than a socially based recommender among American consumers compared to Chinese consumers

#### 2.3 Critiques of Hofstede

In an increasingly borderless world, Hofstede's cultural dimensions have received criticism for being outdated and only sustained by small-scale replications (Dimitrov, 2014; Fang, 2003; McSweeny, 2002). Several scholars have argued that Hofstede's dimensions simplify cultures into arbitrary dichotomies with oppositional poles (e.g., Baskerville, 2003; Fang, 2003; McSweeney, 2002; Oyserman, 2006) when, in fact, cultural values are orthogonal. Meta-analytic studies, for instance, suggest that

have taken a broader approach, this study will follow suit. However, in the likely event that no significant effects are found, it would be important to question the validity of Hofstede's work as cultures change.

IND-COL is presumed to exist to some extent across all societies (Oyserman et al., 2002)<sup>3</sup>.

Further, researchers criticize the cultural dimension for their lack of nuance and sensitivity to cultural change over time, as culture, being of human construction, is subject to revealing subtle changes alongside the progression of people (Baskerville, 2003; Oyserman, 2006). As Hofstede's dimensions fail to account for the ever-changing strides of culture, their relevance to online environments and different generations has been questioned (Yi, 2018).

Considering the arguments that 1) the young generation of Chinese consumers who are most accustomed to RS grew up in a radically different China (Shambaugh, 2013) and 2) societies are not static and are subject to exhibit subtle cultural deviations throughout time (Holt, 1994; Oyserman et al., 2002), it may be interesting to address how values of IND-COL manifest within China. Rather than a broad perspective that all Chinese people are collectivistic, I intend to examine how age may influence preferences for recommender use. New findings revisiting Hofstede's dimensions have questioned their applicability to younger consumers (i.e., college students) in South Korea (N=360), Japan (N=357), the United States (N=406), and Canada (N=372) (Yi, 2018).

The research finds that culture is shifting in different directions, and students from cities in South Korea and Japan exhibit individualistic tendencies, often to a greater degree than their Western counterparts (Yi, 2018). Following this study, I am interested in exploring whether similar effects will be detectable in the Chinese population, with younger people displaying more significant tendencies toward individualism. The rapid changes in Chinese society strengthen my argument for exploring how IND-COL values manifest differently within the culture for younger Chinese consumers. In the following paragraphs, I will describe how China's economic, social, and consumer demographic landscape has changed in recent years.

#### 2.4 Machine Learning Recommender Systems

In 2009, Netflix offered \$1 million to anyone who could demonstrate a 10% improvement to their machine learning recommender algorithm. This may seem like a startling sum for simply tweaking an algorithm. Still, it is nothing compared to the value of Netflix's recommendation engine, which is estimated to be worth over \$1 billion annually (McAlone, 2016).

<sup>&</sup>lt;sup>3</sup> Based on this observation, I am also interested in within-culture differences in China (i.e., are younger people more individualistic?)