Temporal perspective on the gender-related difference in online learning behavior

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Abstract

Although several studies suggested considering gender in online learning, the literature about how male and female students would behave is fragmented. Little attention has been paid to the effect of gender on online learning behavioral patterns. This study aimed at investigating the roles of gender in online learning behaviors by analyzing the gender-related difference of students' online learning behavioral patterns. We used the case study approach with descriptive statistical analysis, lag sequential analysis, and temporal log data analysis to investigate gender-related differences in students' online learning behaviors. The results indicated no significant difference in the counts of occurrence of online single learning behaviors between female and male students. However, differences were observed in online learning behavior patterns and how the online learning activities were performed over time. Females were more active in learning behaviors associated with achievement reports and peer list viewing. They tended to view their achievement reports before starting the main course learning activities, indicating that female students might not be more achievement-oriented. The findings provide further insights from a temporal perspective about how gender is associated with online learning. Implications on designing personalized online learning interventions based on considering gender-related differences are also discussed.

Keywords: gender, online learning behaviors, lag sequential analysis, temporality, difference

1. Introduction

The COVID-19 pandemic has emphasized the importance of online learning, especially during crises, and that this learning mode will be essential in future learning environments under the post-COVID era. This calls for more research on improving the quality and outcomes of online learning (Huang et al., 2020). Personalization can be one of the strategies to enhance online learning, where the students' individual characteristics are considered. One of these characteristics is gender, which can have a variety of influences on learning. Gender can affect information processing and cognition: males often makes a judgement based more on a subset of highly available and salient cues in the message. In contrast, more females attempt to assimilate all detailed information before making a judgement (Putrevu, 2001). Gender can also affect interests towards online learning: females report a higher situational interest than males in multi-media online learning which combines animation, narration, and texts (Dousay & Trujillo, 2018). Prior studies also report gender has an effect on the perceived self-efficacy toward the use of online technology in favor of males (Yukselturk & Top, 2012). Last, gender moderated the relationship between tool interactivity and social presence in online learning (Park & Kim, 2020).

Therefore, considering gender difference when designing learning and instruction is crucial for better catering to students' individual needs and optimize their learning process and outcomes, hence enhance satisfaction (González-Gómez et al., 2012). However, how to design personalized learning based on gender can be challenging since there is no consensus on the effects of gender on online learning. Several studies found that gender did affect online learning (Chyung, 2007; Gunn et al., 2003; Price, 2006; Rovai & Baker, 2005; Sullivan, 2001; Taplin & Jegede, 2001), while others did not find a significant gender effect on online learning (Astleitner & Steinberg, 2005; Dousay & Trujillo, 2018; Lu et al., 2003; McSporran & Young, 2001; Park & Kim, 2020; Yukselturk & Bulut, 2007). To better understand how learning occurs in online settings, there is a need to study how online learning occurs in the different gender groups of students by acknowledging that learning in nature is a temporal process occurring over time (Lämsä et al., 2021).

Online learning environments can generate high-resolution data associated with different learning behaviors. These behaviors and the corresponding data make it meaningful to explore the temporal aspects of learning, providing valuable insights about the features of the learning processes beyond only investigating learning outcomes (Knight, Wise, & Chen, 2017). Since only few studies have investigated how gender is associated with the temporal aspects of learning, this study extends the current literature and explores the role of gender in online learning behavioral patterns over time. The aim is to explore Chinese students' online learning behavioural patterns, and how behavioural patterns emerge over time, and how gender was associated with these patterns in an online course. Particularly, this study relies on a set of analysis methods, including Lag Sequential Analysis (LSA) that aims to model user behaviors and identify behavioral patterns that occur at frequencies greater than chance (Knight, Wise, & Chen, 2017; Sackett, 1979; Zhang et al., 2019).

The remainder of this paper is structured as follows: Section 2 presents the theoretical framework and literature background of this study, while Section 3 identifies the research gap and its purpose. Section 4 discusses the followed research methodology. Section 5 presents the obtained results, while Section 6 discusses them. Finally, Section 7 summarizes the contribution of this study, with the implications and future directions.

2. Literature Review

2.1. Social Role Theory explaining Gender-related Differences and Similarities

To examine and explain gender-related behavioural differences in online learning, this study refers to Eagly & Wood (2012)'s Social Role Theory. This theory considers that gender-related similarities and differences arise primarily from the distribution of men and women's social roles in a specific society. It consists of a set of causes, from immediate causes (i.e., gender role beliefs) to ultimate causes (i.e., division of labor), which can help explain gender-related differences and similarities in affect, cognition, and behaviour. Each of them is described below.

First, gender role beliefs are the proximal factors leading to gender-related differences in affect, cognition, and behavior. It's a shared belief that more women than men occupy the roles facilitated by communal behaviors, domestic behaviors, sub-ordinate behaviors. In contrast, men occupy more roles requiring agentic behaviors, resource acquisition behaviors, or dominant behaviors. According to Wood and Eagly (2012), gender roles influence behavior through a bio-social mechanism involving hormonal changes, socio-structural factors of gender identity (motivating responding through the self-regulatory process), and other stereotypic expectations.

Second, labor division, an outcome of the interaction between the physical specialization of the sexes and local conditions, is an ultimate factor determining gender-related difference. This labor division comes from the evolved physical difference between the sexes, for example, women's strength in reproductive activities and men's greater size and strength, interacting with the demands of people's economic and social environment (Wood and Eagly, 2002). In addition to labor division, greater power or status were ceded to men by societies, contributing to gender hierarchy, which serves as the middle-level causes of sexed-differentiated behaviors (Eagly & Wood, 2012).

As learning is also a social activity, gender differences have impacted the way male and female learners behave, as discussed in the next section.

2.2. Gender and Online Learning

Previous studies reported conflicting findings of the effect of gender on online learning, and thus the results related to gender effect are not conclusive (Cuadrado-García, Ruiz-Molina, & Montoro-Pons, 2010; Dousay & Trujillo, 2019; Yukselturk & Bulut, 2009). On the one hand, several studies found that gender did not have a significant effect on online learning. For instance, Astleitner and Steinberg (2005) suggested that the gender effect on online learning outcomes was not significant. Linnenbrink-Garcia, Patall, and Messersmith (2013) found no statistically significant differences based on gender in a summer science program. Yukselturk and Bulut (2009) found no significant gender differences exist in motivational beliefs of self-regulated learning and achievement in programming.

On the other hand, other studies (Ashong & Commander, 2012; Chanlin, 1999; Chyung, 2007; Gunn et al., 2003; McSporran & Young, 2001; Price, 2006; Rovai & Baker, 2005) found a gender-related difference in online learning. For instance, Chanlin (1999) suggested that females are more interested in relationship building and gaining feedback, whereas males are more interested in achievement successes. González-Gómez et al. (2012) found that females were more satisfied in online learning than males, and females perceived more importance of learning planning and help-seeking. Females were also more motivated to learn and better at communicating online and managing their learning tasks than males (McSporran & Young, 2001). In contrast, males exhibited a higher level of perceived attention problems (e.g., perceived attention discontinuity, lingering thoughts, and social media notification) than females (Wu & Cheng, 2019). Males' higher orienting problems were associated with more negative self-esteem. However, for females, higher perceived attention problems were associated with poorer academic achievement (Wu & Cheng, 2019). As a result, males often needed more discipline offered by the class. To self-regulate their attention, males applied more behavioral strategies over social media use when disorientation increased during online searches, while females used more versatile strategies (Wu & Cheng, 2019).

Considering online learning performance, Nistor (2013) asserted that females tend to participate more actively and intensively in online learning (i.e., more counts of student-generated learning task content). Male students’ attitudes toward online learning display higher stability than female students’ learning attitudes. Such gender effect can be explained by female’s higher motivation to comply with gender-specific roles in social interaction set forth by society. However, Park and Kim (2020) further found that male students benefited more from the use of interactive communication technologies and perceived more satisfaction in online learning. Regarding teacher support, females had higher positive perceptions than males (Ashong & Commander, 2012). Yukselturk and Bulut (2009) found that female students' achievements were more affected by anxiety tests in online contexts. However, male students' achievements were more affected by self-efficacy and task value.

The possible reasons why gender-related differences exist in online learning might be because females and males think, feel, and behave differently with technology as each gender has different technology use preferences, habits, and computer literacy characteristics (Luik, 2009). For example, female students tend to use technology specifically for learning purposes as opposed to most male students, who tend to use technology as an enjoyable activity (González-Gómez et al., 2012; Luik, 2009; Nistor, 2013). However, few studies have investigated how students use technologies and behave in online learning settings (Yeung et al., 2021), and the effect of gender on underlying mechanisms of online learning are largely unknown, calling for more investigation (Felnhofer et al., 2014; Park & Kim, 2020). In this study, we adopted the temporal perspective of learning to address this research gap and provide insights on the current conflicting findings of the effect of gender on online learning.

In addition, the influence of gender on online learning can be affected by many other factors grounded in the broad social contexts, which are mostly documented in education in the west (Li & Kirkup, 2007). For example, gender's effect can be further different across different cultures since gender is a social construct and varies across cultures (Neculaesei, 2015). In China, the current study context, Zhou (2014) examined Chinese students' efficacy about using internet to seek information and their search process and outcomes. Zhou found a gender gap in online learning behaviors is diminishing in the new Chinese generation, which was most salient in average-performing students. For average-performing groups, male students perceived a higher level of self-efficacy in their online searching abilities than female students. Males were also more engaged in search activities than females. Zhai et al. (2018) found that male students favor procedure feedback and female students prefer conclusive assessments in the context of online self-regulated learning. Authors (2021) found a gendered-related difference in Chinese students' transitional patterns in online learning behaviors.

3. Research gap and the purpose of this study

The results of investigating the effect of gender in online learning are not consistent and are even conflicting (Cuadrado-García, Ruiz-Molina, & Montoro-Pons, 2010). This calls for more research on this topic. Additionally, traditional methods like surveys and tests have frequently been used in this type of study (see Wu & Cheng, 2019; Park & Kim, 2019). However, tests can measure learning outcomes but fall short of providing an in-depth understanding of the learning process; surveys can obtain students' subjective perceptions, which may cause response bias (Lavrakas, 2008). Additionally, most studies that investigated gender's effect on online learning based on analyzing students' learning data focused mainly on single or isolated behaviors, such as students' regulative behaviors (Yukselturk & Bulut, 2009) and computer usage and interaction (Ashong & Commander, 2012). However, single or isolated behaviors cannot reflect the students' cognitive engagement and learning behavior characteristics in a comprehensive way (Shang, Xiao, & Zhang, 2020).

Many researchers have thus highlighted the importance of investigating the temporal aspects of learning (Knight, Wise, & Chen, 2017; Lämsä et al., 2020; Yang, Wang, & Li, 2016). Therefore, this study focuses on analyzing the gender-related difference in students' online learning behavioral patterns based on LSA and temporal log data analysis (TLDA). These methods provide different perspectives on the temporality of learning: order of events in a short temporal context (LSA) and characteristics of events over time in a long temporal context (TLDA, Lämsä et al., 2020; 2021). Specifically, this study answers the following Research Questions (RQs). In addition, for any identified gender-related difference in online learning behaviors, we explain the results from a broad perspective of Social Role Theory.

RQ1. What kinds of online learning behavioral patterns do occur during a semester-long course, and how is gender associated with the patterns?

RQ2. What kinds of differences in online learning behavior do emerge between male and female students over time?

4. Methodology

4.1. Study design, context, participants, and case description

For the study design, we used an exploratory case study (Yin, 2014). An asynchronous online course, "Design and Learning," offered by a large university in north China in 2019, was chosen as the study context. The online course was for six weeks. It was provided via the Moodle Learning Management System (LMS). The course's goal was to prepare students who enrolled in an international competition hosted by the chosen university, and this competition focused on Design for Future Education. The course aimed to help students develop the essential knowledge and skills about educational technology and design-related theories. Completing the course was mandatory for the competition registers; however, the students could drop out of the course whenever they want. Additionally, it was explicitly stated that taking or not this course will not affect the university grades. Students who enrolled in this course were all Chinese first-year undergraduate students aged between 18 and 20 and majoring in Education. In total, 200 Chinese students enrolled in this study, and 120 of them completed the entire course, including 42 males and 78 females. The whole class with these 120 students was used as a single case to examine the temporal aspects of students' online learning.

The students were requested to set up their profiles on the LMS when they registered for the course. The profile included information like students' full names, university, gender, and background. The profile aimed to encourage students to learn about their peers, get a sense of community, and seek support when needed. Every week, the students watched instructional videos, read written materials, and uploaded assignments. Once the students completed a content module, they automatically earned a badge. Students could also check their achievement reports and their peers' reports generated by the LMS to know the number of completed modules, learning progress, and their achieved grades. The students could also use the course forum to ask questions and communicate with their peers. When needed, the teacher prompted students and helped them by joining forum interactions.

4.2. Data Collection and the Coding Schema

Students' activities were automatically captured and stored as log data in Moodle LMS. These data were exported into MS Excel files. After data cleaning, 12427 pieces of log data generated by the 120 students were obtained. Three researchers coded these data, following the coding schema in Table 1. Each of the learning behaviors was assigned a code. Examples of these 17 types of activities were also provided, as shown in Table 1. In the last column, the behavior types were further grouped based on the extent to which they were related to each other. A coding agreement was reached via coders' discussions for any discrepancy in generating the categories shown in the last column in the coding schema and classifying learning behaviors into these categories.

Table 1. *The coding schema*

Code	Behavior	Example	Category
A	Course module searched	The user with id '484' has searched the course with id '10' for forum posts containing ''.	Course module activity
B	Course module viewed	The user with id '498' viewed the 'forum' activity with course module id '154'.	
C	Course module completion	The user with id '428' updated the completion state for the course module with id '135' for the user with id '428'.	
D	Submission form viewed	The user with id '403' viewed their submission for the assignment with course module id '164'.	Assignment submission
E	Submission upload	The user with id '638' has uploaded a file to the submission with id '1570' in the assignment activity with course module id '164'.	
F	Submission updated	The user with id '450' updated a file submission and uploaded '1' file/s in the assignment with course module id '164'.	
G	Comment created	The user with id '499' added the comment with id '18' to the submission with id '993' for the assignment with course module id '127'.	Forum interaction
H	Discussion created	The user with id '498' has created the discussion with id '62' in the forum with course module id '154'.	
I	Discussion subscription created	The user with id '388' subscribed the user with id '388' to the discussion with id '64' in the forum with the course module id '154'.	
J	Discussion viewed	The user with id '403' has viewed the discussion with id '72' in the forum with course module id '175'.	
K	Comment deleted	The user with id '435' has deleted the discussion with id '38' in the forum with course module id '154'.	
L	The list of peers is viewed	The user with id '633' viewed the list of users in the course with id '10'.	Peers
M	Peers' profile is viewed	The user with id '635' viewed the profile for the user with id '635' in the course with id '10'.	
N	Peers' course report is viewed	The user with id '487' has viewed the user report for the user with id '487' in the course with id '10' with viewing mode 'discussions'.	
O	The collected badge is viewed	The user with id '610' has viewed the list of available badges for the course with the id '10'.	Achievement result view
P	A personal course report is viewed	The user with id '479' viewed the user report for the course with id '10' for user with id '479'.	
Q	Grade report viewed	The user with id '484' viewed the overview report in the gradebook.	

4.3. Data Analysis Methods

The temporal analysis of learning aims to describe learning as a process that unfolds and occurs over time and, thus, to illustrate the temporal nature of learning (Knight, Wise, & Chen, 2017). We define the analysis of the temporal aspects of learning as focusing on the characteristics of or interrelations between learning-related events over time (Lämsä et al., 2021). In online learning contexts, an event may refer to a single learning behavior, such as uploading submission, creating comments, or deleting comments. The focus on the characteristics of the events over time refers to the passage of elapsed time (Blikstein, 2011; Haythornthwaite & Gruzd, 2012). So that, for example, the content, rate, or duration of the events over time are studied within a course (Haythornthwaite & Gruzd, 2012). The focus on the interrelations between the events over time can refer to the order of events without the information about when the behavioral patterns emerge (Biswas et al., 2010; Halatchliyski et al., 2014; Knight et al., 2017; Lämsä et al., 2021). Considering the purpose of this research, we examined the temporal aspects of learning by focusing on the online learning behaviors over time (passage of time -interpretation) and online learning behavioral patterns (order of events -interpretation).

Online learning provides a suitable context for the temporal analysis of the learning process due to the possibility of having detailed information on students and their behaviors over time through their log data. For modeling user experience, Log Data (LD) and Lag Sequential Analysis (LSA) are two of the approaches that have been used within the technical domain of learning analytics. Much emphasis has been placed on the application of LSA, as it can be used to process log data with a high temporal resolution for studying the under-examined temporal aspects of learning (Knight, Wise, & Chen, 2017). For example, Chen, Resender, Chai, and Hong (2017) conducted LSA and found that the specific behavioral patterns in online knowledge-building discourse characterized more productive discussion threads. LSA has also been used to identify students' unique behavioral patterns that could assist teachers in providing personalized feedback when needed (Hwang & Chen, 2017). LSA has also revealed instructors' discussion patterns during problem-solving and students' behavior patterns in a mixed mode of asynchronous and synchronous discussions (Hou, Sung, & Chang, 2009). Moreover, LSA has also been applied to examine the relationship between students' interaction patterns and learning outcomes by comparing the learning behaviors of high and low achievement students (Cheng, Wang, Cheng, & Chen, 2019). Since LSA is based on the order of events -interpretation on the temporality, passage of time- interpretation on log data could provide complementary information on the temporal differences between male and female students (cf. Lämsä et al., 2020).

For the analysis methods, descriptive statistics were first calculated, including the mean value, standard deviation, and the summed value of each behavior type for males and females. T-tests for examining the differences in the counts of occurrence of single learning behaviors were then implemented using the SPSS software.

To answer RQ1 and to identify the behavioral patterns of the whole class (i.e., the whole students in the online course) and the difference between males and females, LSA was applied using the software GSEQ (5.1). LSA aims at detecting significant behavioral patterns, where a sequence must have a z-score higher than 1.96 (Bakeman & Quera, 1995). Conducting LSA assumes that the total number of behavior samples should be more than six times of all possible behavioral patterns (Bakeman & Gottman, 1997, p. 125). In this study, 17 types of learning behaviors resulted in 289 (i.e., 17x17) possible behavioral patterns. Based on the descriptive statistics calculated, the whole class, female group, and male group, correspondingly, had 12423, 7941, and 4484 samples. Each of them is more than 1734 (six times of 289), meaning there was sufficient data for conducting LSA.

To answer RQ2, temporal log data analysis (TLDA) was applied (Lämsä et al., 2020). We considered the timestamps of online learning behaviors (see Table 1) and plotted empirical cumulative distribution functions (ECDFs) by using R software. ECDFs were plotted for the male and female students in terms of all the online learning behaviors and then separately for the different clusters of the learning behaviors. The value of the ECDF indicates the fraction of the learning events that have been performed in a given instant of time (Lämsä et al., 2020). We also calculated the maximum distance (D) between the male and female students that indicates how similarly or differently the students behaved over time.

5. Results

5.1. Descriptive statistics and comparison based on T-tests

Descriptive statistics of the counts of each type of learning behavior's occurrence were calculated, as shown in Table 2. The results indicated that the occurrence of each learning behavior type varied, with the total counts ranging from 6 to 4740 and the percentage ranging from 0.03% to 38.14%. The results show that Behaviors B "Course module viewed" (38.14%) and C "Course module completion" (34.30%) were the most frequently occurred behavior types (indicated by the icon " ↑ "). It is therefore suggested that viewing and completing course modules were the most basic online learning behaviors in this course. Behavior types with intermediate occurrences (indicated by the icon "-") included Behaviors D "Submission form viewed" (6.32%), J "Discussion viewed" (5.73%), L "The list of peers is viewed" (5.36%), E "Submission upload" (4.81%), and M "Comment deleted" (2.09%). Finally, behavior types with few occurrences. For example, Behavior types A "Course module searched" (0.05%), G "Comment created" (0.03%), K "Comment deleted" (0.06%), and N "Peers' course report is viewed" (0.09%) rarely happened (" ↓ "). Small counts of searching, commenting, deleting comments, and viewing peers' reports suggested that students rarely conducted these types of social activities. T-tests indicated no significant difference ($p > .05$) in the occurrence of every single behavior between male and female students.

Table 2. *The descriptive statistics of the frequency of each type of learning behaviors grouped by gender*

Behavior		Females				Males				Sum_ total	Percentage
		N	Mean	SD	sum_f	N	Mean	SD	sum_m		
B	↑	78	37.23	35.18	2883	42	43.74	43.68	1857	4740	38.14%
C	↑	78	34.56	27.11	2682	42	36.62	26.78	1581	4263	34.30%
D	--	78	6.29	6.84	488	42	7.00	9.36	298	786	6.32%
J	--	78	6.56	11.39	506	42	4.86	9.37	206	712	5.73%
L	--	78	6.90	16.98	529	42	3.29	9.12	137	666	5.36%
E	--	78	5.12	4.43	383	42	5.00	4.51	215	598	4.81%
M	--	78	2.97	12.02	231	42	0.69	1.44	29	260	2.09%
P	↓	78	0.96	2.57	72	42	1.14	2.99	47	119	0.96%
I	↓	78	0.73	1.80	57	42	0.83	2.02	35	92	0.74%
H	↓	78	0.33	0.75	26	42	0.57	1.67	24	50	0.40%
F	↓	78	0.41	0.86	32	42	0.29	0.77	13	45	0.36%
O	↓	78	0.24	0.59	19	42	0.48	1.13	19	38	0.31%
Q	↓	78	0.19	0.56	14	42	0.29	0.74	12	26	0.21%
N	↓	78	0.14	0.83	11	42	0.00	0.00	0	11	0.09%
K	↓	78	.06	0.34	5	42	0.05	0.31	2	7	0.06%
A	↓	78	0.01	0.11	1	42	0.12	0.63	5	6	0.05%
G	↓	78	0.03	0.16	2	42	0.05	0.22	2	4	0.03%
Total		N/A			8017	7941			4410	12427	100%

5.2. What kinds of online learning behavioral patterns do occur during a semester-long course, and how is gender associated with these patterns?

LSA was first conducted at the class level (i.e., the whole students in the online course) to detect significant transitional sequences, where a sequence must have a z-score higher than 1.96 (Bakeman & Quera, 1995). See Appendix A. The students' online learning behavior patterns were mapped in Figure 1. The thicker the lines, the higher the significance value of the pattern.

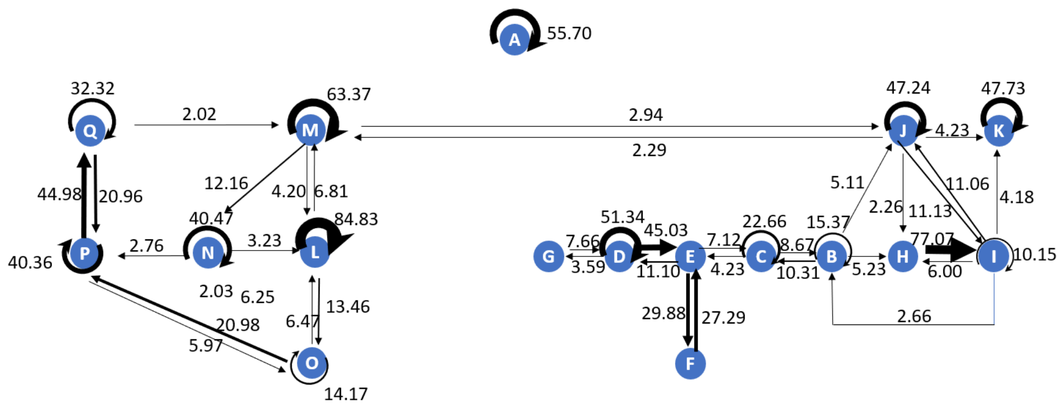

Figure 1. Online learning behavioral patterns of all students

After analyzing the behavioral patterns of all students (presented in Figure 1), three behavioral pattern clusters emerged (see Figure 2), namely: (1) cluster 1 focused on viewing achievement reports and the lists of peers. It included the behavior types O, P, Q, L, M, N; (2) cluster 2 focused on course module activity and assignment submission. It included the behavior types G, D, E, C, B, F; and, (3) cluster 3 focused on forum interaction, and included the behaviors types H, I, J, and K. Finally, behavior A (Course module searched) emerged as an isolated behavior. It is seen that students at the class level transited from Cluster 1 to Cluster 3 and from Cluster 3 to Cluster 2 mutually, suggesting students' forum interaction connected course module learning activities and viewing achievement reports and peers.

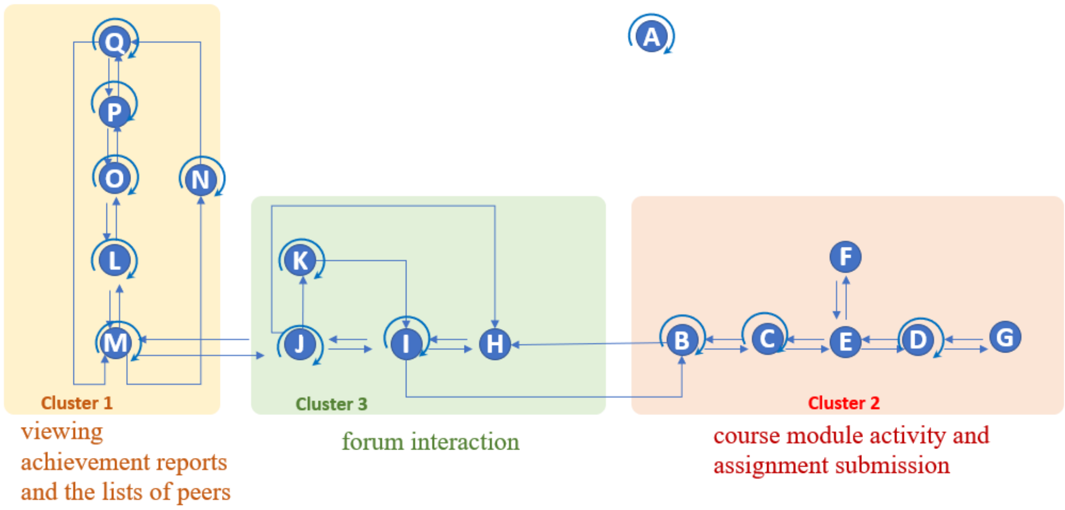

Figure 2. Three online learning behavioral pattern clusters.

LSA was then conducted for male and female students separately. Figure 3 shows those behavioral patterns which reached a significant effect (z-score higher than 1.96). See these Z scores in Appendix B and Appendix C. The thicker the lines, the higher the significance value of the pattern.

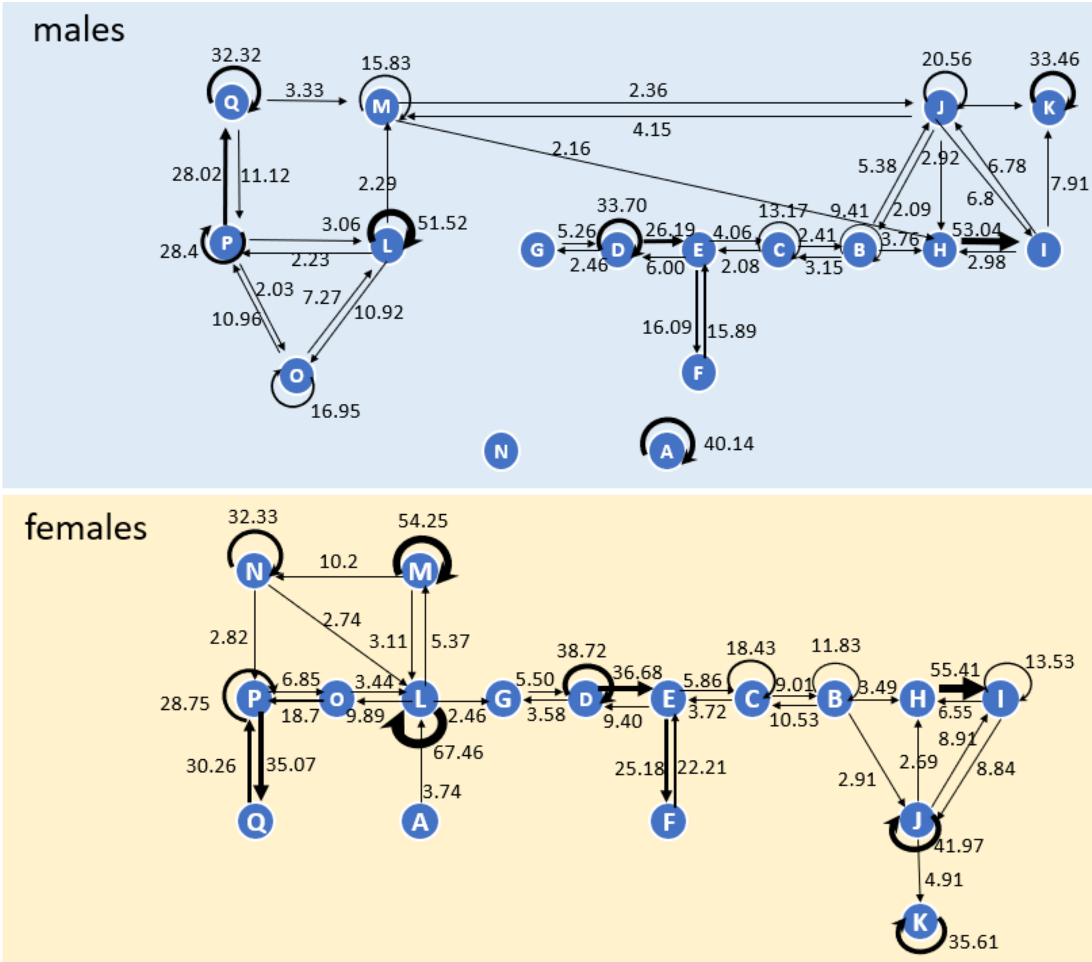

Figure 3. Online learning behavioral patterns of males and females

The two behavioral pattern diagrams of females and males were further re-structured and juxtaposed, as shown in Figure 4. Accordingly, several similarities were identified, namely: (1) for both male and female students, three major online learning behavior Clusters (1, 2, and 3) of online learning behaviors emerged; (2) they both had behavioral patterns from cluster 2 to cluster 3, indicating that they tended to complete course module learning and assignment activities and then joined the discussion activities; and, (3) within the cluster of the course module learning and assignment activities (cluster 2), the behavioral patterns of male and female students were exactly the same.

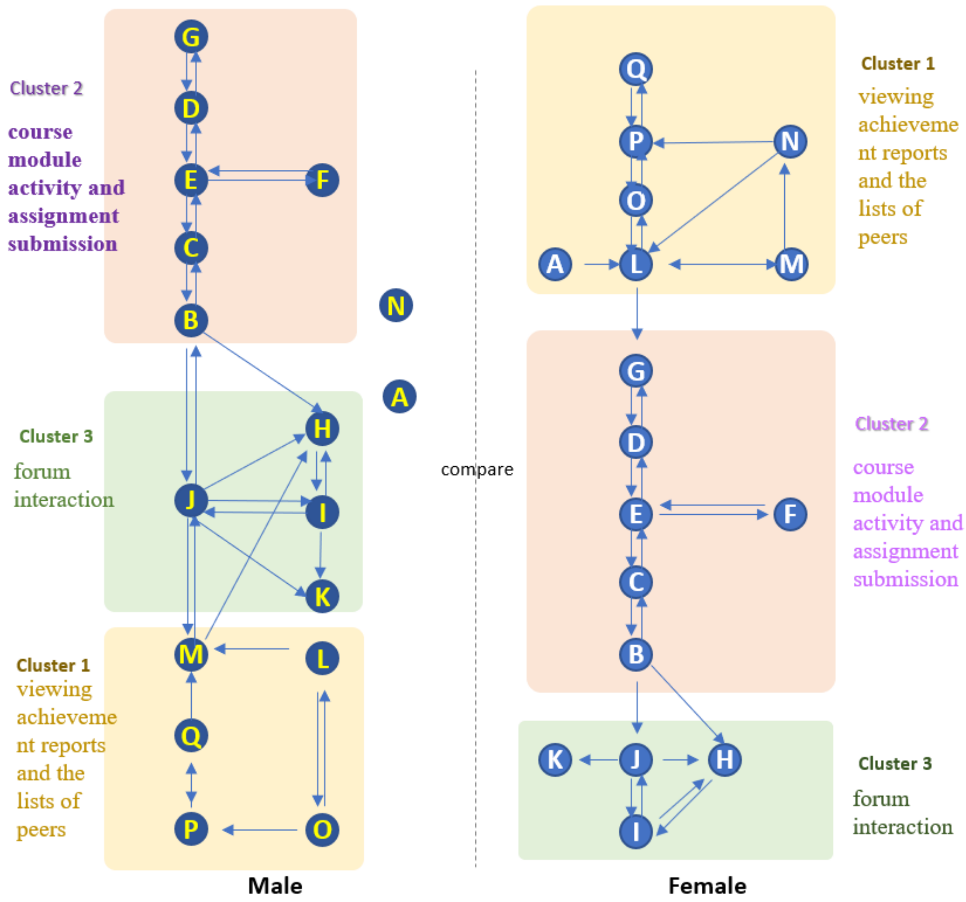

Figure 4. Three online learning behavioral pattern clusters of females and males

The observed differences at the levels of behavioral patterns and behavioral pattern clusters between male and female students are detailed in Table 3. Such decisions were made according to the results of checking whether there were significant transitional patterns (Z>1.96) between any two types of behaviors within a specific cluster or across clusters (see Figure 4). For example, for males, there is no significant link between Cluster 1 "view achievement reports and the lists of peers" and Cluster 2 "course module learning and assignment activities," since there were no significant transitional patterns (Z>1.96) found between any activities from Cluster 1 and activities from Cluster 2. The Z scores of transitional behaviors were calculated and presented in Appendix A (for females) and B (for males).

Table 3.

The differences in behavior transitional patterns between male and female students

Level	Male-specific pattern	Female-specific pattern
Cluster	There is no significant link between cluster 1 "view achievement reports and the lists of peers" and cluster 2 "course module learning and assignment activities."	Females demonstrated a transitional pattern (clusters 1→2), meaning their course learning and assignment activities (cluster 2) were more likely to happen after visiting their peers or their achievement reports.
	Males demonstrated a mutual transitional pattern between clusters 2 "course module learning and assignment activities" and 3 "forum interaction."	Females had a behavior cluster transition (cluster 2→3), but there is no behavior transition (cluster 3→2).
Behavior	Males had several unique transition patterns (J "Discussion viewed" → B "course module viewed"; Q "Grade report viewed" →M "Peers' profile is viewed"; I "Discussion subscription created" → K "Comment deleted").	Females had unique transition patterns (P "a personal course report viewed" → O "the collected badge is viewed"; N "peer's course report viewed" → P "a personal course report viewed"; A "course module searched" → L "The list of peers is viewed").

5.3. What kinds of differences in online learning behavior do emerge between male and female students over time?

The plotted empirical cumulative distribution functions (ECDFs) indicate that the overall temporal similarities and differences in online learning behaviors between males and females, as shown in Figure 5. At the early beginning and the very end of the course, male and female students were almost equally active in their learning activities. As time passed, the temporal differences between the male and female students' behaviors emerged; females were more active in the learning activities than males, and the highest difference $D = 0.11$. This difference was maintained for a long period in the middle of the course, and it then waned and disappeared at the end of the course.

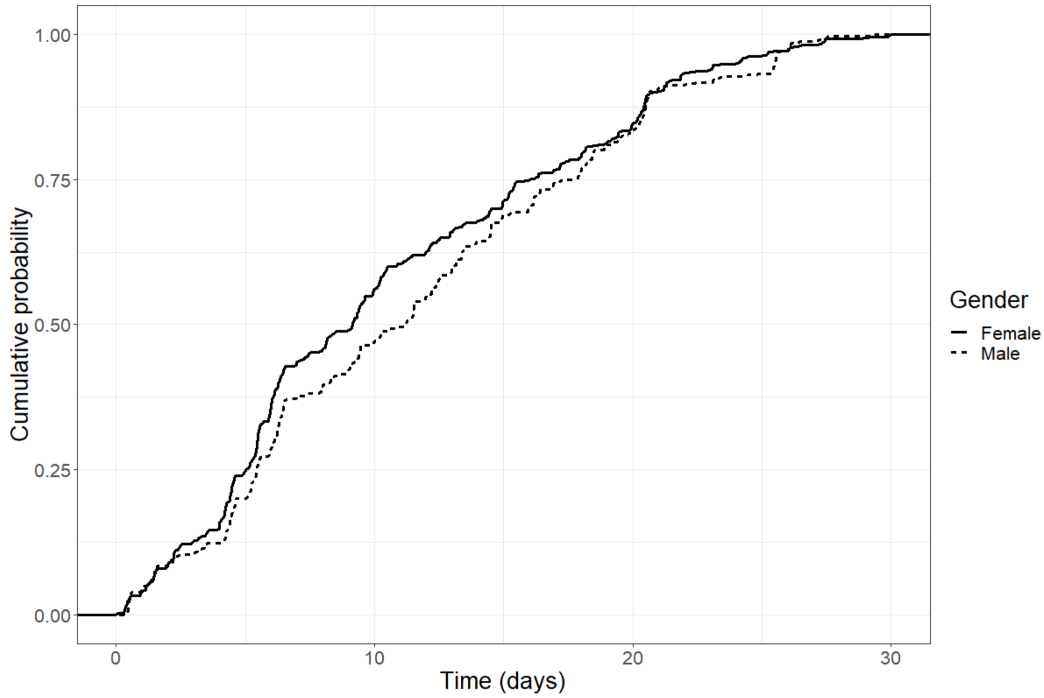

Figure 5. Empirical cumulative distribution functions (ECDFs) of the relative number of online learning events for the male and female students. In the given instant of time, the value of the function is equal to the fraction of the total number of the events that have been performed before that time instant.

In order to examine the identified overall temporal difference in Figure 5, further analysis was conducted by considering the three learning behavior clusters, as shown in Figure 6.

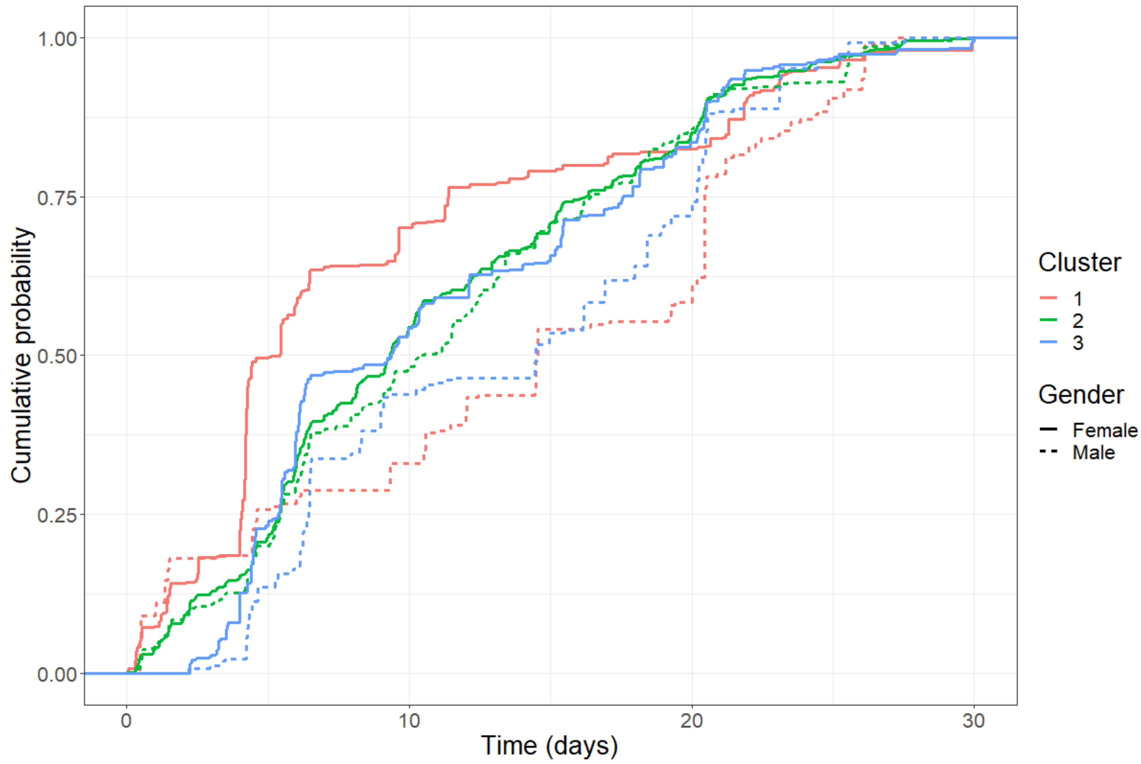

Figure 6. Empirical cumulative distribution functions of the online learning event clusters in the groups of male and female students.

For cluster 1 (viewing achievement reports and the lists of peers), the difference between the two gender groups was largest (the largest distance *D* = 0.39) among the three clusters. The difference emerged at the beginning and was sustained in the middle of the course, where females were more active than males. At the very beginning and end of the course, the two groups behaved similarly. At specific time points, such as day 2, males even outperformed females slightly.

For cluster 3 (forum interaction), at the beginning of the course, neither male nor female students performed activities that were associated with the forum interaction. The differences emerged as time passed by, where the female students were more active in participating in the forum interaction during the first three weeks. Compared to clusters 1 and 2, the difference related to this cluster was intermediate (the largest distance *D* = 0.24).

For cluster 2 (course module activity and assignment submission), there was a minor difference observed between males and females (the largest distance $D = 0.09$). Females were slightly more active than males most of the time in the course process. Only at some time points, such as day 19, males behaved more actively than females.

In sum, the temporal differences between gender groups varied across the online learning behavior clusters. For achievement-related activities and social activities, females were more active than males. However, there was only a slight difference between the male and female students for the most basic course activities like viewing course materials and assignment submission.

6. Discussion

This study aimed to explore the temporal differences of online learning between male and female students from two perspectives, namely: online learning behavioral patterns which were investigated by conducting LSA (RQ1), and online learning behavior over time which were investigated by conducting TLDA (RQ2). The comparison based on T-tests indicated no significant differences in the occurrence of single learning behaviors between males and females, which is similar to Linnenbrink-Garcia, Patall, and Messersmith (2012). Moreover, both males and females had three clusters of online learning behavioral activities and the behavioral patterns related to how they got involved in the course module activities and assignment submission (cluster 2) were similar across the gender groups. Both gender groups also had similar involvement features at the very beginning of the course. Remarkably, the pattern related to how they got involved in the course module activities and assignment submission was similar across the gender groups. This evidence indicated that course module activities and assignment submission are basic learning activities. All students got involved in these basic activities in the same style regardless of their features, such as gender and even cultural background. It’s possible that as time passes by, the gender gap in online learning behaviors is being reduced in the new generation of Chinese students (Zhou, 2014).

Even though the temporal perspective on course module activity and assignment submission (cluster 2) did not show differences between the male and female students, there were temporal differences in terms of the online learning behavior activities of clusters 1 and 3 (viewing achievement reports and the list of peers; forum interaction; see Figures 4 and 6). This is basically consistent with the findings in one prior study in China by Authors (2021). Moreover, this study went one step further than Authors (2021) and indicated that as the learning process progressed, females were more active than males, particularly for the activities involving viewed achievement and peers and forum interaction. Females tended to view the list of their peers and their achievement reports before transiting to viewing the course module and doing assignment activities. Females also especially viewed their own course reports and then transited to viewing their badges of course completion. This evidence shows that females in online learning might be more achievement-driven and socially active.

This achievement-oriented feature may relate to females' significantly higher level of achievement orientation (Boyd, 2017). Females also use technological tools more for specific tasks, compared to most male students, who mostly use tools for fun (Nistor, 2013). Female students' active social behavior may be driven by their better verbal skills (Panlan, 2003), their motivation to comply with social interaction roles set by the society (Nistor, 2013), and preference in building relationships and gaining feedback about their performance (Dousay & Trujillo, 2019). The observed behavioral difference can be further caused by the distribution of male and females’ social roles in a specific society according to Social Role Theory (Eagly & Wood, 2012). There is a shared belief that women occupy more roles related to communal behaviors while men get involved roles with agentic behaviors (e.g., self-directed behaviors). Women involved in communal behaviors might lead to their more active engagement with social communications in online learning.

Females' achievement-oriented and socially active behavioral patterns further contributed to their overall more active involvement than males. In contrast, males demonstrated less active participation in achievement-oriented and social activities, which was followed by an overall less active participation in the whole course (see Figure 5). Online learning is a self-regulated learning context that requires learners to manage a variety of learning resources. Traditionally, it is believed females have the related experiences of organizing family matters and management of domestic events from the perspective of Social Role Theory, different from males who get more involved in agentic activities, resource acquisition activities, or dominant activities (Eagly & Wood, 2012). Such gender-related differences in labor division and female-specific advantages may help females better cope with management challenges in online learning (McSporran & Young, 2001) and thus perform more actively than male students.

Male students demonstrated a unique behavioral pattern of transition from forum discussion to course learning activities (cluster 3→2). More specifically, they viewed discussions and then reviewed course modules (J→B); They also uniquely subscribed to discussions and then deleted their comments (I→K); Males also had other behavioral patterns, such as viewing their grades reports and then viewing peers' profiles (G→M), suggesting a feature of social comparisons regarding achievement. These findings indicate that males not only intentionally interacted with peers based on what they learned from their course activities but also were good at actively making use of forum interaction to inform their own course learning activities.

7. Conclusions, Implications, and Limitations

This study reported that gender was not significantly associated with the occurrence of single online learning behaviors but was associated with the temporal differences in online learning behavioral patterns (RQ1) and how the different online learning behaviors were performed over time (RQ2). Social Role Theory and a set of factors, such as preferences in the purpose of technology use, achievement orientation, the motivation of online learning, and communication skills, could be the potential mediating factors for these findings.

The obtained findings can help explain the potential mechanism of how gender affects online learning. For instructional designers, online instructors, and even LMS designers, the findings shed light on designing personalized online learning based on considering the features of learning activities and gender differences. For example, males should be directed to get involved in social interaction. Customized supports, such as scaffolding prompts, should be provided to male students during online learning to make them be more aware of their achievement and involvement. In contrast, females might need to be reminded to use the takeaway from social interaction and inform their course learning activities.

This study also has some limitations that should be acknowledged. For instance, the sample size of both males and females was unbalanced. Additionally, this study covered only male and female genders, and no other genders were considered. Furthermore, we only examined the gender-related difference in learning behaviors with Chinese students. As a result, the role of culture was not considered, which threatens the results of this study. Future work could involve more participants to duplicate this study in different cultural contexts and use other research methods, such as interviews, to reveal the underlying factors of gender-related differences. Based on our findings, personalized learning supports based on gender differences can be developed and validated to make personalized online learning more effective.

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Availability of data and materials.

The datasets used during the current study are available from the corresponding author on reasonable request.

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Appendix A. *Z-score of navigational behaviors of all students*

Given:	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
A	55.7	-0.22	-1.78	-0.64	-0.56	-0.15	-0.04	-0.16	-0.21	-0.61	-0.06	1.23	-0.36	-0.07	-0.14	-0.24	-0.11
B	0.6	15.37	10.31	-10.95	-19.62	-5.28	-0.54	5.23	-6.27	5.11	-2.08	-16.72	-9.19	-1.99	-2.93	-5.81	-3.69
C	-1.77	8.67	22.66	-13.87	4.22	-4.86	-1.45	-5.12	-6.96	-19.89	-1.91	-17.73	-10.49	-2.4	-4.18	-6.02	-3.35
D	-0.64	-17.29	-20.47	51.34	45.03	-1.75	3.59	-1.84	-2.5	-6.55	-0.69	-6.89	-3.16	-0.86	-1.63	-1.73	-0.56
E	-0.55	-7.66	7.12	11.1	-4.58	29.88	-0.45	-1.59	-2.17	-6.03	-0.6	-3.54	-3.34	-0.75	-0.66	-0.76	-1.17
F	-0.15	-5.23	-4.25	-1.15	27.29	-0.41	-0.12	-0.43	-0.58	-1.67	-0.16	-1.6	-0.97	-0.2	-0.38	-0.66	-0.31
G	-0.04	-1.56	-1.45	7.66	-0.46	-0.12	-0.04	-0.13	-0.17	-0.5	-0.05	-0.48	-0.29	-0.06	-0.11	-0.2	-0.09
H	-0.16	-4.64	-5.14	-1.85	-1.62	-0.43	-0.13	-0.45	77.07	-1.76	-0.17	-1.69	-1.03	-0.21	-0.4	-0.7	-0.33
I	-0.21	2.66	-6.98	-2.52	-2.2	-0.58	-0.17	6	10.15	11.06	4.18	-2.29	-0.66	-0.29	-0.54	-0.95	-0.45
J	-0.6	-1	-17.75	-4.18	-6.29	-1.66	-0.49	3.13	11.13	47.24	4.23	-4.14	2.26	-0.82	-0.85	-1.14	-1.28
K	-0.06	0.28	-1.92	-0.69	-0.61	-0.16	-0.05	-0.17	-0.23	0.96	47.73	-0.63	-0.38	-0.08	-0.15	-0.26	-0.12
L	-0.58	-15.87	-18.32	-5.47	-6.07	-1.6	1.74	-1.69	-2.29	-6.4	-0.63	84.83	6.81	-0.79	13.46	1.86	-0.38
M	-0.36	-6.21	-11.3	-2.46	-3.73	-0.98	-0.29	-0.05	-1.41	-0.28	-0.39	4.2	63.37	12.16	-0.91	-1.61	-0.76
N	-0.07	-1.96	-2.41	-0.87	-0.76	-0.2	-0.06	-0.21	-0.29	0.47	-0.08	3.23	1.64	40.47	-0.19	2.76	-0.15
O	-0.14	-2.12	-4.14	-1.61	-1.41	-0.37	-0.11	-0.39	-0.53	-1.53	-0.15	6.47	-0.9	-0.18	14.17	20.98	-0.29
P	-0.24	-4.16	-7.18	0.53	-2.51	-0.66	-0.2	-0.7	-0.95	-2.72	-0.26	1.89	-0.94	-0.33	5.97	40.36	44.98
Q	-0.11	-1.14	-3.29	-1.33	-1.17	-0.31	-0.09	-0.32	-0.44	-1.27	-0.12	-0.34	2.02	-0.15	-0.29	29.6	-0.24

Appendix B.

Z-score of navigational behaviors of female students

Given:	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
A	-0.01	-0.75	-0.72	-0.26	-0.23	-0.06	-0.02	-0.06	-0.09	-0.26	-0.03	3.74	-0.17	-0.04	-0.05	-0.1	-0.04
B	1.32	11.83	10.53	-7.61	-15.05	-4.28	-1.07	3.5	-4.61	2.86	-1.69	-14.04	-9.02	-1.88	-2.34	-4.58	-2.39
C	-0.71	9.01	18.43	-10.25	3.72	-4.05	-1.01	-3.65	-5.41	-16.61	-1.6	-15.67	-10.06	-2.37	-2.63	-4.2	-2.77
D	-0.26	-12.46	-15.85	38.72	36.68	-1.45	2.58	-1.31	-1.94	-5.23	-0.57	-6.09	-2.79	-0.85	-1.12	-1.73	-0.99
E	-0.23	-5.59	5.86	9.4	-4.37	25.18	-0.32	-1.15	-1.71	-5.05	-0.5	-3.68	-3.13	-0.75	-0.98	0.23	-0.87
F	-0.06	-4.24	-3.31	-0.72	22.21	-0.36	-0.09	-0.32	-0.48	-1.49	-0.14	-1.51	-0.97	-0.21	-0.28	-0.55	-0.25
G	-0.02	-1.06	-1.01	5.5	-0.33	-0.09	-0.02	-0.08	-0.12	-0.37	-0.04	-0.38	-0.24	-0.05	-0.07	-0.14	-0.06
H	-0.06	-3	-3.66	-1.31	-1.17	-0.32	-0.08	-0.29	55.41	-1.34	-0.13	-1.36	-0.88	-0.19	-0.25	-0.5	-0.22
I	-0.09	0.99	-5.43	-1.95	-1.74	-0.48	-0.12	6.55	13.53	8.84	-0.19	-2.02	-0.5	-0.28	-0.37	-0.73	-0.33
J	-0.26	-2.33	-14.82	-3.69	-5.35	-1.48	-0.37	2.69	8.91	41.97	4.91	-3.82	0.7	-0.87	-0.2	-1.3	-1.01
K	-0.03	0.19	-1.6	-0.57	-0.51	-0.14	-0.04	-0.13	-0.19	1.23	35.61	-0.6	-0.38	-0.08	-0.11	-0.22	-0.1
L	-0.27	-13.38	-16.21	-4.81	-5.48	-1.51	2.46	-1.36	-2.02	-6.07	-0.6	67.46	5.37	-0.89	9.89	0.97	0
M	-0.17	-6.51	-10.63	-2.03	-3.55	-0.98	-0.24	-0.88	-1.31	-1.33	-0.39	3.11	54.25	10.2	-0.76	-1.5	-0.67
N	-0.04	-1.85	-2.38	-0.85	-0.76	-0.21	-0.05	-0.19	-0.28	0.36	-0.08	2.74	1.24	32.33	-0.16	2.82	-0.14
O	-0.05	-0.87	-2.64	-1.12	-1	-0.28	-0.07	-0.25	-0.37	-1.15	-0.11	3.44	-0.75	-0.16	-0.21	18.7	-0.19
P	-0.1	-1.92	-5.36	-0.23	-1.96	-0.54	-0.14	-0.49	-0.72	-2.24	-0.21	0.57	-0.75	-0.32	6.85	28.75	35.07
Q	-0.04	-2.24	-2.68	-0.96	-0.86	-0.24	-0.06	-0.21	-0.32	-0.98	-0.09	0.07	0.96	-0.14	-0.18	30.26	-0.16

Appendix C.

Z-score of navigational behaviors of male students

Given:	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
A	40.14	-0.05	-1.66	-0.6	-0.51	-0.12	-0.05	-0.16	-0.2	-0.49	-0.05	-0.4	-0.18	0	-0.15	-0.23	-0.12
B	-0.07	9.41	3.15	-8.12	-12.65	-3.04	0.25	3.76	-4.31	5.38	-1.19	-8.55	-1.14	0	-1.95	-3.63	-2.92
C	-1.65	2.41	13.17	-9.42	2.08	-2.67	-1.04	-3.63	-4.38	-10.88	-1.04	-8.2	-2.82	0	-3.31	-4.41	-1.96
D	-0.6	-12.23	-12.99	33.7	26.19	-0.96	2.46	-1.31	-1.59	-3.93	-0.38	-3.16	-1.44	0	-1.2	-0.63	0.23
E	-0.5	-5.29	4.06	6	-1.8	16.09	-0.32	-1.1	-1.33	-3.31	-0.32	-0.62	-1.21	0	0.04	-1.53	-0.78
F	-0.12	-3.01	-2.68	-0.97	15.89	-0.19	-0.08	-0.26	-0.32	-0.79	-0.08	-0.64	-0.29	0	-0.24	-0.37	-0.19
G	-0.05	-1.18	-1.05	5.26	-0.32	-0.08	-0.03	-0.1	-0.13	-0.31	-0.03	-0.25	-0.11	0	-0.09	-0.14	-0.07
H	-0.16	-3.68	-3.64	-1.32	-1.12	-0.26	-0.1	-0.36	53.04	-1.08	-0.1	-0.87	-0.4	0	-0.33	-0.5	-0.25
I	-0.2	2.98	-4.4	-1.6	-1.35	-0.32	-0.13	1.89	-0.53	6.78	7.91	-1.05	-0.48	0	-0.4	-0.6	-0.31
J	-0.49	2.09	-9.7	-1.96	-3.34	-0.79	-0.31	1.85	6.8	20.56	-0.31	-2.18	4.15	0	-0.98	-0.08	-0.76
K	-0.05	0.26	-1.05	-0.38	-0.32	-0.08	-0.03	-0.1	-0.13	-0.31	33.46	-0.25	-0.11	0	-0.09	-0.14	-0.07
L	-0.4	-7.98	-8.45	-2.5	-2.7	-0.64	-0.25	-0.87	-1.05	-2.62	-0.25	51.52	2.29	0	10.92	2.23	-0.62
M	-0.18	0.79	-3.61	-1.45	-1.23	-0.29	-0.11	2.16	-0.48	2.36	-0.11	1.22	15.83	0	-0.36	-0.55	-0.28
N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
O	-0.15	-2.24	-3.24	-1.17	-0.99	-0.24	-0.09	-0.32	-0.39	-0.96	-0.09	7.27	-0.35	0	16.95	10.96	-0.23
P	-0.23	-4.26	-4.8	1.07	-1.57	-0.37	-0.15	-0.51	-0.61	-1.52	-0.15	3.06	-0.56	0	1.74	28.4	28.02
Q	-0.12	0.63	-1.97	-0.93	-0.79	-0.19	-0.07	-0.25	-0.31	-0.76	-0.07	-0.61	3.33	0	-0.23	11.12	-0.18