



# An investigation of the social influence processes of flipped class students: An application of the extension of the technology acceptance model

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## Abstract

Universities are increasingly incorporating flipped learning as an effective instructional approach. Given the popularity of flipped learning, numerous studies have examined the psychological aspects of students and learning achievement in flipped learning classes. However, little research has examined the social influence processes of students in flipped class. This study investigated the effects of social influence processes (i.e., subjective norm, image, and voluntariness) on students' perceived usefulness of and intention to register for flipped learning using the extension of technology acceptance model (TAM2). A total of 306 undergraduates who took flipped classes participated in this research. The primary research findings indicated that subjective norm influenced perceived usefulness and intention to register for flipped classes. However, image did not influence perceived usefulness or intention to register for flipped classes. Voluntariness affected perceived usefulness and influenced intention to register for flipped classes through perceived usefulness.

**Keywords** Flipped learning · Technology acceptance model 2 · Social influence processes · Perceived usefulness · Intention to register

## 1 Introduction

Flipped learning has gained increasing attention from scholars and educators after research has shown that it can promote learning engagement and student achievement (O'Flaherty & Phillips, 2015; Strelan et al., 2020). Thus, an increasing number of universities have adopted flipped classes as an effective learner-centered

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instructional approach (Fulton, 2012; Greener, 2015; Lee et al., 2022). In addition, when schools unexpectedly and suddenly closed during the COVID-19 pandemic, online learning, flipped learning, and blended learning became popular teaching formats in higher education (Divjak et al., 2022; Hew et al., 2020; Mali & Lim, 2021; OECD, 2021). According to UNESCO (2020), more than 1.5 billion students in 165 nations were affected, forcing a sudden switch to online formats during the COVID-19 pandemic. As a result, many instructors and administrators were introduced to and became interested in incorporating flipped learning into their online and hybrid courses (Jia et al., 2023). According to Research and Markets (2023), the estimated market size of flipped learning in 2022 was around 1.9 billion US dollars, and it is expected to grow to 4.5 billion US dollars by 2028.

Ng (2018) described flipped learning as an instructional approach in which students study pre-learning materials (often online) at a convenient time prior to the regular class time. The students can then be deeply engaged in thought-provoking learning activities in the class based on what they learned from the pre-learning materials. Bergmann and Sams (2012) and Fulton (2012) pointed out that the strength of flipped learning is that it encourages students to actively participate in the class which leads to high learning engagement. Huang et al. (2023) also emphasized that incorporating flipped learning in a class can enhance students' learning motivation and learning engagement.

Al-Samarraie et al. (2020) conducted a systematic review of flipped learning implementation in higher education contexts and found that flipped learning promoted students' learning engagement, attitudes, metacognition, performance, and learning outcomes across disciplines. However, little is known about students' perspectives. Given that many higher education institutions and instructors are increasingly offering and teaching flipped classes, it is vital that students perceive that flipped learning is a beneficial approach compared to more traditional instructional approaches (i.e., instructor-led classes). A distinct feature of flipped learning is that students are required to study pre-session materials (e.g., pre-class videos) or activities prior to regular class time. Hence, students may have different perspectives of flipped learning courses compared to traditional classes in terms of the workload and time requirement for learning (Ng, 2018). Huang et al. (2023) and Koh (2019) indicated that students who were enrolled in flipped learning classes perceived that they were given more homework or there were more requirements than in traditional classes. Another difference between flipped learning and traditional classroom learning is the pre-class activities in flipped learning classes. Förster et al. (2022) asserted that learners' engagement in pre-class activities is important for successful in-class sessions as well as for the overall learning outcomes in flipped learning classes.

Instructors and university administrators are well aware of the advantages of flipped learning, including the pedagogical strengths and cost-effectiveness in implementing student-centered instructional approaches to an increasing number of students with limited national and institutional funds (O'Flaherty & Phillips, 2015). However, students may be influenced by several factors when they decide whether or not to take courses with a flipped class format. Influential factors may include the opinions of important referents (e.g., parents, instructors) about flipped learning, or the quality or competitiveness of flipped class students. However, a key question is:

If students could choose between regular classes and flipped classes, what would encourage them to take flipped classes? This study examined the social influence processes of students in flipped classes to understand students' adoption mechanism (or process) of flipped learning by applying the extension of the technology acceptance model (TAM2) (Venkatesh & Davis, 2000).

## 2 Theoretical framework

This study is based on Venkatesh and Davis' (2000) theoretical extension of TAM (TAM2). Based on Davis' (1989) original TAM, which describes the effects of perceived usefulness and perceived ease of use on technology acceptance, Venkatesh and Davis' (2000) theory explained that the social influence processes (i.e., subjective norm, voluntariness, and image) and cognitive instrumental processes (i.e., the perceived ease of use, job relevance, output quality, and result demonstrability) influence user acceptance through perceived usefulness. Based on Venkatesh and Davis' (2000) theory, this study investigated the effects of the social influence processes, such as subjective norm, voluntariness, and image, on perceived usefulness and intention to register for flipped learning classes and to fully comprehend students' perspectives of flipped learning. Although considerable flipped learning research has been conducted on learning outcomes, including learning achievement, learning engagement, and learning satisfaction (Doo et al., 2021; Lee et al., 2022; Jia et al., 2023; O'Flaherty & Phillips, 2015; Shen & Chang, 2023), few studies have investigated how learners choose flipped learning over other instructional approaches, such as traditional classrooms, online learning, massive open online learning (MOOCs), or other self-directed learning. Thus, an important issue is students' perspectives of learner-centered learning approaches because they have more autonomy to choose the types of classes they prefer (Sinclair, 2000). Despite the many advantages of flipped learning, if students decide not to take flipped learning classes, they may lose out on the expected learning gains of flipped learning. Hence, it is necessary to examine students' actual social influence processes in choosing a flipped learning course from their perspective. The findings can help instructors and school administrators who provide flipped learning courses understand students' social influence processes in choosing flipped classes. Understanding students' perspectives will ultimately increase enrollment in flipped learning classes. However, we know relatively little about students' perspectives. To fill this research gap in flipped learning, it is necessary to understand what factors influence a student's decision to enroll in flipped learning classes from a social influence process perspective.

### 2.1 Flipped learning research

Considerable research has been conducted on flipped learning given the growing attention and interest in flipped learning in higher education. Most research has focused on the effectiveness of flipped learning in terms of learning outcomes, learners' psychological status, and instructional design aspects (Cheng et al., 2019; Lee

et al., 2017; O’Flaherty & Phillips, 2015; Sergis et al., 2018; Sletten, 2017; Strelan et al., 2020). For example, Awidi and Paynter (2019) investigated student learning experiences in flipped learning classes with 50 undergraduates enrolled in a flipped learning biology class using a mixed-method approach and found a high level of student satisfaction, confidence in learning, and learning engagement.

Given the importance and increasing popularity of flipped learning, many systematic reviews and meta-analysis studies have recently been conducted. O’Flaherty and Phillips (2015) conducted a systemic review of flipped learning literature and found that flipped learning improved students’ academic performance and instructor satisfaction. Akçayır and Akçayır (2018) conducted a systematic review of flipped learning by analyzing 71 SSCI indexed journal articles. The research findings in these two meta-analyses indicated that the advantages of flipped learning include improving learning performance, satisfaction, and engagement from learning outcome perspectives. They also found that pedagogical contributions of flipped learning include facilitating flexible learning and individualized learning as well as enhanced learner autonomy in the learning process. The challenges of flipped learning include students’ insufficient preparation for in-class sessions and the need for instructors to provide effective instructional guidelines for studying at home. Students and teachers both perceived that flipped learning takes more time with a heavier workload than traditional classroom learning. The technological challenges of flipped learning include producing quality videos for pre-class activities.

Koh (2019) also conducted a comprehensive literature review to examine the current status of flipped learning in higher education. Koh’s research identified four themes of the effectiveness of flipped learning in higher education: (1) personalization, (2) higher-order thinking, (3) collaboration, and (4) self-direction. Across these studies of flipped learning, the research universally has indicated that flipped learning, in general, facilitates students’ learning engagement, perceptions and attitudes toward learning, self-efficacy and metacognition, and performance and achievement. Cheng et al. (2019) also conducted a meta-analysis of 55 papers published between 2000 and 2016 to estimate the effect size of flipped classroom instructional strategies on learning outcomes. They found that the overall effect size of flipped class instructional strategies was small but significant. Strelan et al.’s (2020) recent meta-analysis about the effectiveness of flipped learning reviewed 174 flipped learning studies. They reported a medium effect size of flipped learning ( $g = .50$ ) on learners’ performance and added that flipped learning is effective in all disciplines. A year later, Bredow et al. (2021) analyzed 317 flipped learning studies and found a small to medium effect size of flipped learning ( $g = .39$ ) on academic learning outcomes.

During and after the COVID-19 pandemic, flipped learning has been adapted and become more advanced to meet societal changes. Whereas many flipped learning classes have generally included online pre-class activities and face-to-face in-class session, many courses were designed to be fully online during the pandemic. For example, Jia et al. (2023) designed a fully online flipped learning class because schools were closed during the pandemic. This format presents new and unique flipped learning challenges and benefits for instructors and student engagement. Another challenge and potential benefit in flipped learning classes is the recent rapid advancement in artificial intelligence (AI). For example, Huang et al. (2023) applied

AI technologies in flipped learning classes to provide personal recommendations to enhance learning motivation, and engagement, and improve learning outcomes.

In sum, considerable empirical research has investigated the learning process in flipped learning classes since its emergence, including the influence of psychological aspects of participants, instructional design issues, and learning outcomes (Cheng et al., 2019; O’Flaherty & Phillips, 2015). However, there is a serious lack of research examining the impact of the pre-learning social influence on flipped learners (i.e., the factors that encourage or discourage students from enrolling in a flipped class). Despite the significance of this topic, research on the social influence of flipped learning students has been mostly overlooked. A more thorough understanding of flipped learning is needed to address this research gap. Thus, this study focused on Venkatesh and Davis’ (2000) social influence processes to understand the social influence of flipped learning on students.

## 2.2 An extension of the technology acceptance model

Davis’ technology acceptance model (TAM) (1989) has been applied widely over the last three decades to explain people’s behaviors related to the adoption of innovation or new technologies across disciplines. According to TAM, technology adoption is determined by two main factors: users’ perceived ease of use (i.e., “the degree to which a person believes that using a particular system would be free of effort”) and perceived usefulness (i.e., “the degree to which a person believes that using a particular system would enhance his or her job performance”) (Davis, 1989, p. 320). As for the strengths of the two variables, perceived usefulness has been consistently found to have a stronger influence on technology adoption than perceived ease of use.

TAM has been applied extensively to understand learners’ behaviors in education. Chen Hsieh et al. (2017) applied Davis’ original TAM to examine students’ acceptance of the smartphone application “LINE” in EFL oral training using flipped learning. In particular, they examined the effects of perceived ease of use and perceived usefulness on behavioral intention, and how the perceived ease of use influenced behavioral intention through their attitude toward use. However, they found that perceived ease did not influence perceived usefulness. Perceived usefulness also influenced behavioral intention through the attitude toward use. They also found different path coefficients of TAM depending on the oral English proficiency levels of the students (i.e., high achieving vs. low achieving group). More recently, Han and Sa (2022) applied TAM to examine the acceptance of online classes during COVID-19 in Korea. They surveyed 313 undergraduates who learned fully online due to school closures on students’ perceived ease of use, perceived usefulness, learning satisfaction, and acceptance intention of online classes. The results indicated that students’ perceived ease of use of online classes influenced the perceived usefulness and learning satisfaction, but not their acceptance intention. However, perceived usefulness influenced students’ learning satisfaction and acceptance intention both.

About a decade after the emergence of TAM, Venkatesh and Davis (2000) expanded Davis’ original version of TAM (1989) to improve the explanatory power

by adding key influential external elements of perceived usefulness and intention to use. This extended TAM model (TAM2) includes two sub-processes that influence the constructs of perceived usefulness and intention to use: social influence processes and cognitive instrumental processes (Venkatesh & Davis, 2000). The social influence processes explain the relationships among social forces, such as subjective norm, voluntariness, and image, and estimates the influence on individuals' perceived usefulness and intention to use. In contrast, cognitive instrumental processes illustrate individuals' general cognitive processes leading to their decision-making processes to adopt a new system considering the perceived ease of use, result demonstrability, output quality, and job relevance.

### 2.3 Social influence processes

Social influence processes include three key elements: subjective norm, image, and voluntariness. Subjective norm refers to individuals' perceptions of their expectations from important referents (Fishbein & Ajzen, 1975; Venkatesh & Davis, 2000). That is, when individuals perceive that an important referent thinks that they should adopt a new system, they incorporate the referent's opinion into their own belief structure. Kelman (1958) called this acceptance *Internalization*. Agudo-Peregrina et al. (2014) revised the definition of subjective norm in an e-learning context as "the extent to which a student perceives pressure from members in his or her environment to use e-learning systems" (p. 3) because students' tendency to adopt an e-learning system is influenced by the opinions of peer students, family members, teachers, and educational institution policies.

Voluntariness refers to the extent to which individuals perceive that their decision to adopt new technology or systems is non-mandatory (Agarwal & Prasad, 1997). Numerous studies have reported interesting research findings that subjective norm is influential in a mandatory setting, but not in a voluntary setting (Abdullah & Ward, 2016; Dećman, 2015; Hartwick & Barki, 1994; Schepers & Wetzels, 2007; Sun & Zhang, 2006; Venkatesh & Davis, 2000). Kelman (1958) called this concept *compliance* in his social influence theory, referring to the voluntariness of behaviors. For this reason, in Venkatesh and Davis' (2000) study, voluntariness (i.e., voluntary or mandatory usage) was investigated as a moderating variable of the effects of social norm on intention to use. In addition, Deci and Ryan (2000) explained that people become motivated to perform tasks when their psychological needs, including autonomy, relatedness, and competence are satisfied. A voluntary setting enhances the autonomy of learners and thus it is expected to influence perceived usefulness and intention to use. Davis (1989) emphasized that it is necessary to examine "the conditions and mechanisms" of social influence to understand the effects on behaviors.

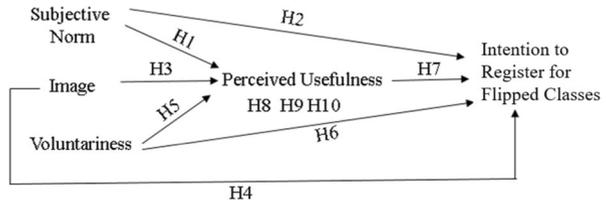
Making or sustaining a good image in an organization is one reason to follow subjective norm. Kelman (1958) called this concept image *identification*, referring to affiliation or membership to become an inner circle member by following the social groups' desirable behaviors. Abdullah and Ward (2016) analyzed 22 studies examining the effect of social influence on learners' e-learning acceptance. Among the 22 studies,

19 (86%) reported a significant impact of social influence on perceived usefulness of e-learning learners, indicating a small-to-medium effect size. Abdullah and Ward (2016) also conducted a systematic review of 107 papers on technology acceptance of e-learning and examined the effects of five external factors related to perceived ease of use and perceived usefulness: (1) social influence/subjective norm, (2) self-efficacy, (3) enjoyment, (4) experience, and (5) computer anxiety. They found that social norm is an important external factor of technology acceptance with significant effects on both perceived usefulness ( $\beta = .301$ ) and perceived ease of use ( $\beta = .195$ ). Schepers and Wetzels (2007) also conducted a meta-analysis on an external factor of TAM2 to investigate the influence of social norm and its moderation effects in TAM by analyzing 63 relevant studies. The research findings indicated large effect sizes between subjective norm and behavioral intention ( $r = .42$ ), and between subjective norm and perceived usefulness ( $r = .40$ ). Tarhini et al. (2013) applied TAM2 to an e-learning environment to examine the effects of social norm, perceived usefulness and ease of use, and quality of work life. They analyzed the survey responses from 569 e-learning students in Lebanon and found that social norm as well as perceived usefulness and ease of use, and quality of work life had significant impacts on behavior intention to adopt e-learning.

Efiloğlu Kurt and Tingöy (2017) also examined the effects of social influence, effort expectancy, and performance expectancy on intention to adopt virtual learning with two sample groups in Turkey and the UK. The effects of social influence on the intention to adopt virtual learning were statistically significant in the two countries and the social influence was the most significant variable to determine the intention to use in Turkey. In addition, van Raaij and Schepers (2008) reported that subjective norm influenced perceived usefulness in the adoption of virtual learning environments in China. Although the subjective norm did not affect the intention to use in virtual learning environments, it indirectly influenced the intention to use through perceived usefulness. Kemp et al. (2021) examined students' acceptance of virtual reality (VR) using TAM by surveying 179 freshmen. The hypotheses examined the influence of social influence, cognitive engagement, and system attributes on the attitude toward VR and behavioral intent of adopting VR through perceived usefulness and perceived ease of use. Social influence affected perceived usefulness of VR, but not perceived ease of use. Perceived usefulness of VR influenced the behavioral intent of adopting VR. More recently, Raffaghelli et al. (2022) applied the unified theory of acceptance and use of technology (UTAUT), an extension of TAM, to explain students' acceptance of an AI-based early warning system in online learning courses in higher education. They measured students' perceived usefulness, expected effort, social influence, facilitating conditions, and trust in pre- and post-usage stages and then compared the changes over time. Their findings indicated that students' perceived usefulness about the early warning system was low. Social influence was expected to be a predictor of acceptance of the early warning system; however, there were no statistical changes in the pre- and post-usage stages.

Based on the previous research findings of TAM2, we present five research questions to investigate the effects of social influence processes on flipped learners. Given that we are investigating students' willingness to register for a flipped class when there is a choice between a flipped learning class and a traditional class, we use the term "intention to register" instead of the original TAM2 term "intention to use."

**Fig. 1** Research model and hypotheses of the study



1. Does subjective norm influence perceived usefulness and the intention to register for flipped classes?
2. Does image affect perceived usefulness and the intention to register for flipped classes?
3. Does voluntariness of flipped classes influence perceived usefulness and the intention to register for flipped classes?
4. Does perceived usefulness affect the intention to register for flipped classes?
5. Does perceived usefulness mediate the relationship between subjective norm, image, and voluntariness and intention to register for flipped classes?

Figure 1 illustrates the research model, and the ten hypotheses of the current study are as follows:

H1: Subjective norm positively influences perceived usefulness.

H2: Subjective norm positively influences intention to register for flipped classes.

H3: Image positively influences perceived usefulness.

H4: Image positively influences intention to register for flipped classes.

H5: Voluntariness positively influences perceived usefulness.

H6: Voluntariness positively influences intention to register for flipped classes.

H7: Perceived usefulness positively influences intention to register for flipped classes.

H8: Perceived usefulness mediates the relationship between subjective norm and intention to register for flipped classes.

H9: Perceived usefulness mediates the relationship between image and intention to register for flipped classes.

H10: Perceived usefulness mediates the relationship between voluntariness and intention to register for flipped classes.

## 3 Methods

### 3.1 Context and participants

The current research was conducted at a large university in Seoul, South Korea in the fall semester of 2019. This university has promoted flipped classes since 2017 to facilitate students' participation in class and to enhance learning engagement and learning achievement. To encourage faculty members and students to adopt flipped learning,

flipped learning courses were allowed to adopt a criterion-referenced grading system while most courses in the university that have employed a norm-referenced grading system (e.g., an A grade is only given to the top 25% of the class). Although using a criterion-referenced grading system does not guarantee that all students will receive good grades, it is an attractive option for choosing flipped learning classes.

The 16-week flipped learning courses included online pre-session learning and face-to-face classes. In these flipped courses, the students were asked to listen to an online lecture at their convenience prior to the once-a-week face-to-face class. In the fall semester of 2019, a total of 39 flipped learning courses were offered across the university. The author contacted nine professors who taught flipped classes with more than 20 students in each class to ask them to disseminate an online survey link to students through Blackboard, the learning management system of the university, or by email. The instructors announced the survey in class and encouraged the students to participate in the study. Participation in the survey did not give students additional course credit nor did it influence the course grade. Thus, the students voluntarily participated in the online survey a week before the final exam. We conducted the survey at the end of semester to ensure that the participants had sufficient experience with flipped learning to answer to the survey questions. The participants of this study were 306 students who were enrolled in flipped classes in the 2019 fall semester (survey response rate: 68.45%). Table 1 presents the participants' demographic information and time spent in pre-class online learning.

**Table 1** Demographic information and time for pre-class learning

Variables	Categories	Percentage
Gender	Male	45.4%
	Female	54.6%
Class years	Freshmen	23.9%
	Sophomores	33.0%
	Juniors	29.7%
	Seniors	13.4%
Majors	Energy resources	16.0%
	Nano-material science	15.7%
	English language and literature	10.8%
	Chemistry	10.1%
	Education	10.1%
	Fashion design	8.8%
	Business administration	7.5%
	Others	21.0%
Time spent studying online pre-session	Less than 30 minutes	21.5%
	30 minutes to 1 hour	32.4%
	1–1.5 hours	22.9%
	1.5–2 hours	12.4%
	2–2.5 hours	4.9%
	2.5–3 hours	2.9%
	More than 3 hours	2.9%

Of the 306 participants, 55.2% answered that they invested more time on the flipped learning classes than regular classes, whereas 11.5% spent less time studying than for regular classes, and 33.3% perceived no difference in the actual study time.

### 3.2 Measurement instruments

The survey consisted of 20 questions: demographic information (6 items) and questions about subjective norm (2 items), image (3 items), voluntariness (3 items), perceived usefulness (4 items), and intention to register (2 items). Demographic information included (1) years of class, (2) gender, (3) major, (4) flipped learning experience, (5) reasons for taking the flipped learning class, and (6) time for learning (on a weekly basis). Except for demographic information, the participants answered each question on a 5-point Likert scale from 1 (i.e., strongly disagree) to 5 (i.e., strongly agree). The participants were also asked an open-ended question about their perception of the required learning time of flipped classes.

We adopted the TAM2 (Venkatesh & Davis, 2000) to measure the five primary variables of this study. The survey questions were modified to make sense for a research context, and then they were reviewed by a professor teaching educational technology at the university where the data were collected. We also asked 22 students who had taken flipped learning classes to review the survey to check for face validity. Subjective norm was measured with two items. Sample questions included, “Professors or my parents, who influence my learning, think that I should take flipped classes” and “My friends or classmates, who are important to me, think that I should take flipped classes.” Image was measured with three items including “The students who take flipped classes seem hard-working or smarter than those who do not” and “Taking flipped classes is very desirable.” Voluntariness was measured with three items: “Taking flipped classes is voluntary,” “Professors or parents do not require me to take flipped classes,” and “Although the flipped classes might be helpful, taking flipped classes is certainly not compulsory.” Intention to register was measured with two items, “I intend to take a flipped class in the future” and “I am willing to participate in a flipped class in the future.” Perceived usefulness was measured with four questions. Sample questions are, “Flipped classes increase my learning productivity” and “Flipped classes improve my learning.” Table 2 presents the measurement scales of this study, including the number of items and the Cronbach’s alphas for the latent variables.

### 3.3 Data analysis

The survey data were analyzed using SPSS (Version 21.0) and Amos (Version 23.0). To judge discrepancies between the data and the proposed model based on Venkatesh and Davis’ (2000) model, the following fit indices for analyses were employed: comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), and a chi-square test. Browne and Cudeck (1993) recommended that CFI and TLI values greater than .90 between the proposed model and the data are considered a

**Table 2** Research Instruments and Correlations

Variables	SN	Image	PU	VOL	IN	Number of items	Cronbach's alpha
Subjective norm	–	.74**	.76**	.40**	.70**	2	.80
Image		–	.56**	.30**	.46**	3	.79
Perceived usefulness			–	.48**	.84**	4	.96
Voluntariness				–	.47**	3	.80
Intention to register					–	2	.96

Adapted and modified from Venkatesh and Davis (2000)

\*\*  $p < .001$ , \*  $p < .05$

good fit. As for RMSEA, a value of .05 indicates a close fit, .08 is a fair fit, and .10 is a marginal fit (Browne & Cudeck, 1993; MacCallum et al., 1996). Hu and Bentler (1999) suggested a cutoff value close to .08 for SRMR.

## 4 Results

### 4.1 Descriptive data

Table 3 presents the descriptive statistics including the means, standard deviations, and the correlations of the measurement variables. Multivariate normality was tested using Mardia's coefficient which is equal to 91.43 and the critical ratio is equal to 37.78. According to Raykov and Marcoulides (2008), multivariate normality is satisfied when Mardia's coefficient is lower than  $p(p+2)$  (i.e.,  $p$  is the number of observed variables). Given that we have 12 observed variables, Mardia's coefficient (i.e., 91.43) is lower than  $p(p+2)$  (i.e., 168). Hence, the multivariate normality assumption was satisfied.

### 4.2 Confirmatory factor analysis results

Confirmatory factor analysis (CFA) was performed using maximum likelihood prior to testing the hypotheses (see Table 4). Based on the convergent validity guidelines by Hair et al. (2006), factor loading values should be higher than .5. The overall CFA results for all factor loadings were over .6, and the measurement model demonstrated a good fit to the data. Convergent validity was examined using composite reliability (CR) and average variance extracted (AVE). The results confirmed that the overall CFA, including factor loadings, AVE, and CR values of the data were all satisfactory.

To assess the discriminant validity, AVE values and the square of the correlations for latent variables were compared (Fornell & Larcker, 1981). Table 5 indicates that the square root of the AVE values for each latent variable was larger than the correlation indicating that the discriminant validity was acceptable.

**Table 3** Descriptive analysis

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Subjective norm 1	1	.67**	.46**	.46**	.51**	.56**	.54**	.54**	.54**	.32**	.20**	.19**	.47**	.49**
Subjective norm 2		1	.53**	.47**	.46**	.60**	.62**	.60**	.61**	.38**	.25**	.21**	.60**	.62**
Image 1			1	.44**	.70**	.39**	.37**	.39**	.35**	.18**	.13**	.16**	.34**	.35**
Image 2				1	.51**	.45**	.50**	.47**	.51**	.27**	.15**	.18**	.47**	.46**
Image 3					1	.43**	.41**	.41**	.35**	.28**	.16**	.21**	.31**	.32**
Perceived usefulness 1						1	.87**	.86**	.79**	.42**	.34**	.22**	.71**	.72**
Perceived usefulness 2							1	.86**	.84**	.43**	.32**	.23**	.76**	.73**
Perceived usefulness 3								1	.84**	.42**	.37**	.27**	.76**	.76**
Perceived usefulness 4									1	.44**	.35**	.26**	.76**	.75**
Voluntariness 1										1	.60**	.52**	.44**	.41**
Voluntariness 2											1	.63**	.37**	.36**
Voluntariness 3												1	.25**	.23**
Intention to register 1													1	.92**
Intention to register 2														1
Mean	3.38	3.24	2.68	3.74	3.06	3.87	3.86	3.87	3.94	3.81	3.93	3.87	3.82	3.88
SD	1.00	1.18	1.11	1.01	1.12	1.06	1.06	1.03	1.03	1.17	1.11	1.5	1.13	1.11
Skewness	-.07	-.14	.19	-.43	.00	-.71	-.75	-.62	-.81	-.74	-.92	-.68	-.78	-.85
Kurtosis	-.17	-.73	-.42	-.42	-.18	-.05	.02	-.23	.19	-.36	-.68	-.19	-.11	.12

\*\**p* < .01, \* *p* < .05

**Table 4** Confirmatory factor analysis results

Latent variable	Measurement variable	Factor loading (> .5)	AVE (> .5)	CR (>.7)
Subjective norm	Subjective norm 1	.779	.647	.785
	Subjective norm 2	.864		
Image	Image 1	.801	.543	.778
	Image 2	.615		
	Image 3	.835		
Perceived usefulness	Perceived usefulness 1	.913	.836	.953
	Perceived usefulness 2	.936		
	Perceived usefulness 3	.933		
	Perceived usefulness 4	.896		
Voluntariness	Voluntariness 1	.740	.532	.772
	Voluntariness 2	.828		
	Voluntariness 3	.720		
Intention to register	Intention to register 1	.963	.904	.950
	Intention to register 2	.956		

**Table 5** Results of discriminant validity assessment

Measures	SN	Image	PU	Vol	Intention	AVE	CR
Subjective norm ( $r^2$ )	–	.74 (.55)	.76 (.58)	.40 (.16)	.70 (.49)	.647	.785
Image ( $r^2$ )		–	.56 (.32)	.30 (.09)	.46 (.21)	.543	.778
Perceived usefulness ( $r^2$ )			–	.48 (.23)	.84 (.71)	.836	.953
Voluntariness ( $r^2$ )				–	.47 (.22)	.532	.772
Intention to register ( $r^2$ )					–	.904	.950

### 4.3 Hypothesis testing results

The statistical significance of each path coefficient among the latent variables was examined using the fitness index. Table 6 indicates that the research model demonstrated a fair fit to the data ( $\chi^2 = 179.301$ ;  $df = 67$ ;  $CMIN/df = 2.676$ ;  $TLI = .956$ ;  $CFI = .968$ ;  $SRMR = .063$ ;  $RMSEA = .074$ ) (Browne & Cudeck, 1993; MacCallum et al., 1996).

The statistical significance of the path coefficient among the variables was examined to test the hypotheses. The results indicated that H1, H2, H5, H7, H8, and H10 were accepted ( $t > 1.96$ ,  $p < .05$ ) as displayed in Tables 7 and 8. Subjective norm had a significant influence on perceived usefulness ( $\beta = .684$ ,  $t = 6.688$ ) and intention to register ( $\beta = .237$ ,  $t = 2.501$ ). Thus, H1 and H2 were supported. Image negatively affected perceived usefulness ( $\beta = -.011$ ,  $t = -.127$ ) and intention to register ( $\beta = -.124$ ,  $t = -1.808$ ), but they were not statistically significant

at  $p < .05$ . Therefore, H3 and H4 were rejected. Voluntariness positively influenced perceived usefulness ( $\beta = .204$ ,  $t = 3.720$ ), but not intention to register ( $\beta = .085$ ,  $t = 1.920$ ). Thus, H5 was supported and H6 was rejected. Perceived usefulness influenced intention to register ( $\beta = .690$ ,  $t = 10.251$ ), indicating that H7 was supported. The results of hypothesis testing are illustrated in Fig. 2.

As Table 7 indicates, the indirect effects of subjective norm, image, and voluntariness on intention to register for flipped classes through perceived usefulness were examined at  $p < .05$ . The results of hypothesis testing indicated that H8 and H10 were accepted, but H9 was rejected. That is, subjective norm and voluntariness influenced intention to register through perceived usefulness; however, the indirect effects of image on intention to register was not observed.

**Table 6** The fitness of the research model ( $N = 306$ )

	$\chi^2$	$p$	$df$	$TLI$	$CFI$	$SRMR$	$RMSEA$ (90% Confidence Interval)
Structural model	179.301	.000	67	.956	.968	.063	.074 (.061 ~ .087)
Fit criteria				> .90	> .90	< .08	< .08

**Table 7** Path coefficient estimates

Hypothesis	$B$	$\beta$	$SE$	$t$ -value
H1: Subjective norm $\rightarrow$ Perceived usefulness	.649	.684**	.097	6.688
H2: Subjective norm $\rightarrow$ Intention to register	.247	.237*	.099	2.501
H3: Image $\rightarrow$ Perceived usefulness	-.012	-.011	.092	-.127
H4: Image $\rightarrow$ Intention to register	-.141	-.124	.078	-1.808
H5: Voluntariness $\rightarrow$ Perceived usefulness	.259	.204**	.070	3.720
H6: Voluntariness $\rightarrow$ Intention to register	.119	.085	.062	1.920
H7: Perceived usefulness $\rightarrow$ Intention to register	.758	.690**	.074	10.251

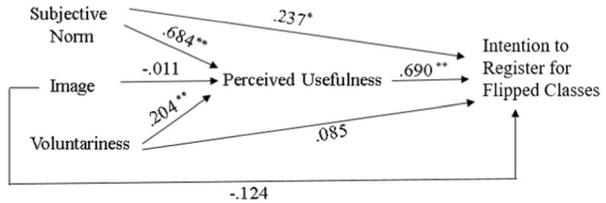
\*\*  $p < .001$ , \*  $p < .05$

**Table 8** Direct and indirect effects of each variable in the hypothesized model

Hypothesis	Total Effects	Direct Effects	Indirect Effects
H8: Subjective norm $\rightarrow$ Intention to register (through PU)	.709	.237	.472*
H9: Image $\rightarrow$ Intention to register (through PU)	-.132	-.124	-.008
H10: Voluntariness $\rightarrow$ Intention to register (through PU)	.226	.085	.141*

\*\*  $p < .001$ , \*  $p < .05$

**Fig. 2** The results of hypothesis testing. Note: \*\*  $p < .001$ , \*  $p < .05$



## 5 Discussion

Flipped learning has received increasing attention in higher education due to its effectiveness in learning achievement and engagement (O’Flaherty & Phillips, 2015; Strelan et al., 2020; Jia et al., 2023). Since flipped learning is a learner-centered instructional approach, students’ perceptions of flipped learning are important for successful implementation (Huang et al., 2023; Koh, 2019). Thus, this study investigated the influences of the social influence processes on students’ perceived usefulness and intention to register for flipped classes using TAM2.

In the social influence process, subjective norm influenced perceived usefulness and intention to register for flipped classes. This finding confirms Venkatesh and Davis’ (2000) research findings on the direct influence of subjective norm on perceived usefulness as well as intention to use and indirect influence of subjective norm on intention to use through perceived usefulness. Subjective norm indicated that the effects of important referents’ opinions, professors’ comments, or the university’s emphasis on the advantages of flipped learning created a favorable image of flipped learning. This research finding confirmed numerous previous research findings (e.g., Abdullah & Ward, 2016; Dečman, 2015; Efiloğlu Kurt & Tingöy, 2017; Schepers & Wetzels, 2007; Sun & Zhang, 2006; Tarhini et al., 2013; Venkatesh & Davis, 2000). In addition to the direct effects of social norm on the intention to register, social norm also indirectly influenced intention to register through perceived usefulness, which supports van Raaij and Schepers’ (2008) research findings.

This study found that subjective norm is a strong influential factor to encourage students to register for flipped learning classes. The practical implications are that it is necessary to promote the strengths and effectiveness of flipped learning to both students and to professors and instructors who are important referents for the students. It is a prerequisite to persuade significant influencers of students to buy into the effectiveness of flipped learning. These important referents of students can exert expert power (i.e., influence based on subject matter expertise) and referent power (i.e., influence based on identification or relationships) as a process of social influence (French & Raven, 1959).

Voluntariness indirectly influenced intention to register for flipped classes through perceived usefulness, but the direct effects were not observed in this study. Given that voluntariness refers to the extent to which individuals perceive that their technology adoption decision is mandatory (i.e., voluntariness), their own decision-making to take flipped classes enhanced students’ perceived usefulness of flipped learning. In other words, when students could make their own choice to take flipped classes (i.e., in a

voluntary setting), students' perceptions of the usefulness of flipped learning increased compared to when the flipped classes were mandatory. Deci and Ryan's (2000) self-determination theory posits that people are more motivated to learn or complete tasks when they have autonomy. Although instructors and university administrators may require students to take some flipped classes, it is necessary to provide students with opportunities to make their own decisions to take flipped classes to enhance their perceived usefulness and increase their intention to register for flipped classes.

Image, an external representation of following social groups' desirable behaviors, negatively influenced intention to register for flipped learning; however, it was not statistically significant. The negative impact of image on the intention to register may be explained by the grading system of the university. If those who take flipped classes are perceived as smart (e.g., *summa cum laude* or *cum laude* students) or flipped learning seems to too difficult or overwhelming, students may be reluctant to register for flipped classes to avoid competition with elite groups of students. In other words, students understand that a good image of flipped learning does not lead to good results (i.e., an A grade) in this unique setting. Davis (1989) emphasized that it is necessary to look at the condition and mechanism of the social influence processes. To enhance students' perceived usefulness and intention to register for flipped classes, it is necessary to help them recognize that flipped classes are beneficial to learning without any personal loss (i.e., high competition or an excessive workload) by implementing a reasonable grading system or suitable class policies for flipped classes. Since 2020 when most classes were online and often incorporated flipped learning formats due to the COVID-19 pandemic, students may now be more comfortable or have different perceptions of the difficulty of flipped learning. The research findings of this study regarding the impact of social influence on perceived usefulness and behavioral intention are consistent with the results of the studies conducted after COVID-19 (e.g., Kemp et al., 2021).

The effects of perceived usefulness on the intention to use were also examined in flipped learning settings. Similar to the research findings of many previous studies (Davis, 1989; Venkatesh & Davis, 2000), the effects of perceived usefulness on intention to use were strongly supported in the current study. Venkatesh and Davis (2000) explained that approximately 60% of intention to use was explained by perceived usefulness in their stepwise regression analysis. The current study confirmed a strong relationship between perceived usefulness and intention to register (Abdullah & Ward, 2016; Schepers & Wetzels, 2007) indicating that it is necessary to emphasize the usefulness of flipped learning in terms of expected improvement in learning achievement, productivity, and engagement to encourage students to register for flipped classes. The results of the current study on the influence of perceived usefulness of online classes on the acceptance intention of online learning are consistent with the findings of Han and Sa's (2022) study, which was conducted after COVID-19. Freshmen orientation programs and flipped learning workshops offered in teaching and learning centers at universities may be good venues to advertise the advantages of flipped learning.

In the present study, we did not examine the actual learning achievement (i.e., grades) of students in flipped learning classes. However, we indirectly asked students about the time required for flipped learning classes and found that 55.2% reported that they spent more time on flipped learning classes than regular classes. That is, approximately half of the students perceived that they worked harder in flipped

learning classes than instructor-led classes. This finding confirmed Koh's (2019) observation about the added time and workload for flipped learning classes. However, as Clark (1983) warned, there is a novelty effect of new media, indicating that when students pay more attention to new technology, which may result in "increased effort or persistence, which yields achievement gains. If they are due to a novelty effect, these gains tend to diminish as students become more familiar with the new medium" (p. 449–450). Thus, it is necessary to observe how students learn in flipped learning classes even after the novelty effect of flipped learning disappears.

People do not make decisions or behave in a vacuum. We constantly and dynamically influence others and are also influenced by others and immediate circumstances. Thus, as Davis (1989) noted, we need to consider the conditions and mechanisms underneath a system for a more thorough understanding of a phenomenon. Schepers and Wetzels (2007) mentioned in their study that to encourage individuals to accept new technology or instructional approaches (e.g., flipped learning), organization-wide (or university-wide) support is critical, including instructor training opportunities, learning and instruction support, and policies and regulations for a favorable learning culture. Sun and Gao's (2019) research also showed that school leadership played a critical role in instructional restructuring (i.e., implementing flipped learning) by building pedagogical and organizational systems for a new learning culture. Lastly, it is necessary to remember Schepers and Wetzels' (2007) warning that "word of mouth" and positive and negative "buzz" through social network service (SNS) are important sources that create subjective norm. This buzz starts with flipped learners' positive learning experience and learning satisfaction.

## 5.1 Limitations and suggestions for future research

The limitations of the current study suggest directions for future studies. The findings lack overall generalizability outside of flipped learning in a Korean context. The various social, cultural, political, and educational factors in Korean society influenced learners' and instructors' flipped learning experiences and expectations. Given that Asian educational systems are highly influenced by Confucianism (i.e., receptive forms of learning), students may have more resistance to this type of active learning and face unique challenges that are not as deeply rooted and experienced in western societies.

Since data collection for this research was across the university with participants in more than ten flipped classes, instructors and the subject matter of the flipped classes were not controlled in this study. To extend and expand the current study, future researchers can include those who have not chosen flipped learning classes as well as students who are not enrolled in flipped learning classes at the time of the survey.

Among the latent variables of the current research, intention to register for flipped classes and subjective norm consisted of only two items, respectively, in the measurement scales of Venkatesh and Davis' (2000) TAM2 instrument. However, the Cronbach's alphas for intention to register (i.e., .96) and subjective norm (i.e., .80) were acceptable and there were no statistical problems with data analysis because of

the two-item scales. Lastly, this research is limited to survey data. Although common method bias was not found in this study, qualitative data obtained from in-depth interviews or focus groups would provide a more comprehensive understanding of the social influence processes of flipped class students. Thus, we encourage future researchers to use a mixed-method approach to extend the current research. Since many universities and students across the globe have gained considerable experience with online learning and new formats such as flipped learning in hybrid courses since the COVID-19 era, it is necessary to conduct comparative research to determine if students' attitudes have changed.

**Data availability** The data used and/or analyzed in the current study are available from the corresponding author upon reasonable request.

## Declarations

**Consent to participate** Verbal informed consent was obtained prior to the survey.

**Conflict of interest** There were no conflicts of interest in this research.

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