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Within-study measurement invariance of the UTAUT instrument: An assessment with user technology engagement variables

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ABSTRACT

We assess *within-study* invariance of key UTAUT scales considering a total of six respondent group characteristics: five variables pertaining to users' two technology engagement facets (prior technology knowledge and technology usage pattern) and one variable pertaining to their gender. Data collected from 250 respondents about their perceptions and usage of online blogs were analyzed to test six invariance hypotheses. The results indicate that the UTAUT instrument showed full or partial invariance for respondents' technology usage pattern and gender. With respect to prior IT knowledge, the UTAUT scales were found to be invariant for general IT knowledge but non-invariant for specific IT knowledge.

1. Introduction

Information technology acceptance and use has a long and rich tradition in the information systems (IS) literature, and it remains a major stream of research in the IS field. Interest in the technology acceptance area has burgeoned since the publication of Davis' [24] Technology Acceptance Model and has led to the development of as many as eight main competing models for predicting technology adoption, acceptance, and usage [62]. To bring coherence to the technology acceptance literature and to provide a unified view of this field, Venkatesh et al. [62] integrated the various competing models into a unified model they termed the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT model consists of four predictor constructs, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions, that predict information technology acceptance and usage [62]. Gender, age, experience and voluntariness of use are moderators of these four predictors of technology usage intention and use behavior. Venkatesh et al. [62] tested their UTAUT model using data from two organizations, and it outperformed the eight other popular technology adoption and acceptance models. Consequently, the UTAUT constructs and related scales[1] have been, and continue to be, widely used in technology acceptance studies for predicting system usage and for making technology adoption and usage-related decisions. It is to be noted that the recent extension of the UTAUT model, the UTAUT2 model by Venkatesh et al. [63], continues to use the four primary predictors of the UTAUT model, thereby further increasing the importance of these four primary predictors.

For an instrument of such import as the UTAUT, it is necessary for the scales in the instrument to exhibit high degrees of psychometric properties as well as measurement invariance. The scales for the UTAUT constructs have been assessed in numerous studies for their psychometric properties, including various types of reliabilities and validities, and have been found to exhibit satisfactory measurement properties (e.g., [1,6,9,15,34,41–43,50,60,62–64]). However, to our knowledge, only three studies [37,39,41] have assessed the UTAUT scales for their measurement invariance, but they have done so in a limited way, as discussed in the literature review section below. These limitations provide the motivation and opportunity for the present study to assess the

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[1] We generally use the term instrument in this paper to refer to a set of measurement scales pertaining to multiple related constructs in a model. However, from a psychometric perspective, an instrument and scale are synonymous terms, and both refer to a set of measurement items for a particular theoretical construct. Therefore, the terms *instrument* and *scale* are sometimes used interchangeably in this paper.

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measurement invariance of the important UTAUT instrument in a comprehensive and rigorous way, as we discuss below.

The purpose of measurement invariance analysis is to establish the invariance or equivalence of an instrument across different respondent groups to ensure that all respondents interpret the focal instrument in a similar way. This analysis assesses the equivalence of the measurement instrument across different respondent groups on a variety of measurement-related criteria, including configural, factor loading, mean, variance, and covariance of latent factors, item intercepts, and random measurement errors [18,19,39]. An instrument that is equivalent in terms of these invariance criteria across different respondent groups is said to be measurement equivalent or measurement invariant, and results for different respondent groups can be compared both within and across studies using the instrument to draw correct and meaningful inferences.

Measurement instruments that are not equivalent across different respondent groups impair the drawing of accurate research conclusions and practical decision-making [29], and they eventually affect the interpretation of research results [18]. Therefore, it is important to establish measurement invariance for all measurement instruments that are used in IS research to derive correct and meaningful conclusions from the study results. It is all the more important to establish measurement invariance for the UTAUT instrument across different respondent groups because these scales continue to be used in a high number of technology acceptance and usage studies in the IS research literature. These studies involve different respondent groups, including, but not limited to, different genders, different nationalities/cultures, different ages, different prior knowledge and different levels of experience with technology. For example, males and females should interpret the UTAUT instruments in a similar manner in order for meaningful and correct conclusions to be drawn about technology acceptance and usage by these two groups of respondents.

As a result, several studies in the technology acceptance and usage literature have conducted invariance testing of the earlier TAM model and its related instruments [5,27,29,40,45,57,58]. However, as mentioned earlier, only three studies have tested the more recent UTAUT model and its related instruments [37,39,41]. While these studies have contributed much to the IS literature in terms of adding to the methodological rigor in technology acceptance and usage research, two gaps in this body of literature pertaining to the UTAUT model provide the motivation and opportunity for the present study.

First, two of the three invariance studies related to the UTAUT perform rather limited invariance analysis, testing only a *few invariance criteria* from among the full suite of invariance criteria (discussed in detail in later sections) [18,19]. Only the study by Kang et al. [39] conducts the full suite of invariance tests on the UTAUT scales, but this study exhibits the second limitation discussed below. This is the first gap in the extant literature the current study seeks to address by **conducting a full suite of invariance tests** in a comprehensive and rigorous manner on five key scales of the UTAUT model.

Second, and perhaps more importantly, as discussed in detail in the literature section, the predominant majority of invariance studies (8 of 10 studies) in the technology acceptance arena, including both the TAM and UTAUT models, have considered respondent grouping (i.e., group-level) variables that allow primarily for the establishment of *across-study invariance* of the UTAUT scales. However, it is also very important to address and establish *within-study invariance* of the UTAUT scales, as respondents within a single technology acceptance study may differ regarding several significant criteria, and it is important that all respondents within a study, regardless of their differences, interpret the UTAUT instrument in a similar manner.

In *across-study invariance*, invariance analysis is performed with group-level variables that typically vary across different studies. For example, a grouping variable like *respondent nationality* generally does not vary within a single study (as data for a single study are generally collected from a single country) but does vary across multiple studies. In other words, there is generally only one value for that variable in a single study. On the other hand, *within-study invariance* is concerned with grouping variables (what we call within-study variables) that vary within a single study. In other words, there will be respondents in a single study sample with varying levels of these group-level variables. For example, within a single study sample, some users will have a low degree of experience in using the focal technology considered in the study, whereas other users will have a high degree of experience with the focal technology. It is quite possible that respondents belonging to the high experience group might interpret the UTAUT instrument differently from the low experience group due to the prior engagement of the former group of users with the focal technology. Establishing within-study invariance is, therefore, essential to ensure that all respondents in a single sample, who may vary on several within-study grouping variables, interpret the UTAUT instrument similarly. Thus, we posit that it is important to establish the *within-study invariance* of the UTAUT instrument in addition to establishing the across-study invariance to ensure that results of any study using the UTAUT instrument are reliable and valid and, thus, interpretable.

In this paper, we study the within-study invariance of the UTAUT instrument with grouping variables that pertain to a *user's engagement with technology*, such as general IT knowledge, knowledge of the focal technology, and frequency of the focal technology usage. These variables generally have multiple values within a single technology acceptance study. We chose user technology engagement variables to establish within-study measurement invariance of the UTAUT instrument because it consists of items that capture technology related perceptions, and respondents with various degrees of engagement with the focal technology might perceive the UTAUT instrument differently. However, there are very few studies – two with the TAM model [29,40] and one with the UTAUT model [41] – that consider prior technology knowledge and technology usage patterns as respondent grouping variables. However, the only study about the UTAUT model with these grouping variables [41] is methodologically limited, as it conducts only configural and metric invariance tests (limitation #1 above). The current study seeks to address this second gap in the extant invariance literature with respect to the UTAUT model and aims to contribute to the **establishment of within-study invariance** of UTAUT scales by focusing on grouping variables that address respondents' engagement with technology.

This study seeks to make two methodological contributions to the technology acceptance research stream. First, we assess the *within-study invariance* of the five key UTAUT scales by conducting a rigorous and comprehensive invariance analysis with a comprehensive set of six grouping variables, five of which capture the key aspects of respondents' engagement with technology in a deep and robust manner. To our knowledge, this is the first invariance study to make a distinction between across-study and within-study measurement invariance and to develop a new and rich understanding of the within-study measurement invariance of the UTAUT instrument. In addition, this is the first study to theorize users' engagement with technology as an important within-study respondent characteristic and then test the within-study invariance of the UTAUT instrument in a rigorous manner by using a state-of-the art invariance testing methodology with a comprehensive set of user technology engagement variables. Furthermore,

Table 1
Summary of invariance studies in technology acceptance.

#	Citation	Variables	Respondent groups based on		Invariance criteria tested
			Across-study variables	Within-study variables	
TAM model invariance analysis					
1	[5]	Perceived manageability, subjective norms, trust beliefs, perceived usefulness	Culture		Metric, structural
2	[27]	Perceived usefulness, perceived ease-of-use, intention to use	Type of application		Configural, metric, structural weights
3	[29]	Perceived usefulness, perceived ease-of-use	Type of application	Gender, prior general experience with computing	Configural, metric, uniqueness
4	[40]	Perceived usefulness, perceived ease-of-use, attitude toward use, intention to use		Gender, age, IT competence	Configural, metric, uniqueness, invariance in factor variance, latent means, structural weights
5	[45]	Perceived usefulness, perceived ease-of-use, intention to use	Culture		Structural weights
6	[57]	Perceived usefulness, perceived ease-of-use, attitude toward use, intention to use	Culture		Configural, metric, scalar, invariance in factor variance, latent means, structural weights
7	[58]	Perceived usefulness, perceived ease-of-use, perceived risks, purchase intention	Culture		Configural, metric, scalar, structural weights
UTAUT model invariance analysis					
1	[37]	Performance expectancy, effort expectancy, facilitating conditions and social influence	Culture		Structural weights
2	[39]	Performance expectancy, effort expectancy, facilitating conditions and social influence	Nationality, type of technology	Gender	Full suite of invariance tests including configural, metric, uniqueness, scalar, latent factor means, latent factor variance, latent factor covariance
3	[41]	Performance expectancy, effort expectancy, facilitating conditions and social influence		Gender, general computing knowledge, particular weblog knowledge, experience with weblogs, frequency of weblog use	Configural and metric

in addition to the first contribution, this study makes a subsidiary second contribution by pointing out the user technology engagement variables for which the UTAUT scales are invariant and those for which one or more of the UTAUT scales are non-invariant. The study also indicates items for all five UTAUT scales that are found to be invariant and that can be used safely in future technology acceptance studies to generate valid and comparable results across different respondent groups.

The rest of the paper is organized as follows. We first present an overview of the measurement invariance literature in the next section. We then discuss the notion of user technology engagement and related grouping variables, followed by the research methodology. We then present and discuss the results of this study. We conclude by discussing the limitations and contributions of the study and outline some future research directions.

2. Literature review

Several IS scholars have performed measurement as well as structural[2] invariance analyses with TAM and UTAUT models. Table 1 provides a summary of the technology acceptance studies that have analyzed the invariance of one or more TAM/UTAUT scales, the main constructs analyzed, the respondent group characteristics used for invariance analysis, whether those grouping variables are within-study or across-study grouping variables, and the invariance criteria tested. The objective of our literature survey is to identify gaps in the literature on invariance analyses of technology acceptance models. In line with this objective, we restrict our literature survey in Table 1 to technology acceptance studies that conduct some type of invariance analysis. It should be noted that some studies in the IS literature have performed invariance analysis on models and scales other than technology acceptance models in the IS domain (e.g., [26,28]), and these studies are not included in Table 1. There are also some invariance studies that test the invariance properties of models in other domains, such as marketing [25,52], psychology [53,54], and healthcare [51], and they are also not included in our review below. Several studies in the IS literature also assess the various types of validities and reliabilities of the technology acceptance model scales with different technologies, such as course management software [43], information kiosks [64], tablet PCs [6], ubiquitous computing [34], mobile commerce [67] and cross-cultural contexts [49]. However, these studies do not test the invariance properties of the TAM/UTAUT model scales and are therefore also excluded from Table 1.

In this section, we elaborate on the two gaps in the literature in this area that we earlier discussed in Section 1. First, except for Kang et al. [39], the other two UTAUT invariance studies do not perform the full suite of invariance criteria established by Cheung [18] and Cheung and Lau [19]. Second, and perhaps more importantly, 8 of the 10 invariance studies in the technology acceptance arena, including both the TAM and UTAUT models, have considered the culture/country/nationality and technology/application used by the respondents as the two key respondent grouping variables that distinguish among/between different respondent groups. As shown in Table 1, cross-cultural invariance analyses have compared technology acceptance models among countries such as the UK and China in the context of online shopping [58]; Korea and the U.S. [37,39] and the UK and Saudi Arabia in the context of internet banking acceptance [5]; Singapore and Malaysia [57]; and a comparison of several countries [45]. However, a typical technology acceptance study generally contains respondents only from one country/nationality/culture and focuses typically on one specific technology/application. Thus, these studies contribute to the assessment of

[2] Structural invariance addresses the invariance of the causal model across different respondent groups.

across-study invariance of the scales tested but do not contribute to the assessment of within-study invariance of the UTAUT constructs.

Although some studies have considered respondent group characteristics such as gender [29,39,40], IT competence [40], age [40], and prior general experience with computing [29] that can help establish within-study invariance of TAM/UTAUT scales, there is still a paucity of invariance studies that test the invariance of the five main constructs of the UTAUT model. Four of the 10 invariance studies of the TAM and UTAUT models assess the invariance of model scales based on gender as a respondent grouping variable [29,39–41], but only two studies assess the invariance of TAM constructs based on general computing knowledge/IT competence as a respondent grouping variable [29,40]. There is only one study, by Li and Kishore [41], of the 10 invariance studies that tests the UTAUT scales with variables that distinguish respondents in terms of their prior knowledge with technology as well as the respondents' technology usage patterns. However, this study is limited methodologically because it conducts only configural and metric invariance tests. On the other hand, the invariance study of the UTAUT model by Kang et al. [39], while methodologically comprehensive (see above), contributes primarily to establishing across-study invariance, as it tests for invariance across countries and technologies. Moreover, the within-study invariance of the UTAUT scales is established by their study only with respect to gender and not with regard to any other respondent grouping variable, including respondents' prior knowledge and/or their technology usage patterns.

The above limitations necessitate a study of measurement invariance of the UTAUT scales based on important within-study respondent group characteristics that distinguish among/between respondents in a single technology acceptance study. Specifically, respondent characteristics that pertain to users' engagement with technology, such as prior technology knowledge and technology usage patterns, are quite important in this context, as respondents necessarily vary in these variables within every single technology acceptance study sample. However, user technology engagement variables have not been used in the extant literature to establish the within-study measurement invariance of the UTAUT instrument using the full suite of invariance tests. The current study seeks to address this gap in the extant invariance literature with respect to the UTAUT model and aims to contribute to the establishment of **within-study invariance** of the UTAUT instrument by focusing on grouping variables that address **respondents' engagement with technology**. We next discuss the notion of and suitable variables with respect to respondents' engagement with technology.

3. Respondents' engagement with technology

We posit that variables pertaining to a respondent's engagement with technology are key within-study variables that will play an important role in the respondent's interpretation of the UTAUT instrument. Almost all technology acceptance research always involves respondents who have different levels of engagement with the focal technology within a single study. Some respondents in a study may be current users of the focal technology, while others may be considering adopting and using it. In addition, respondents within a study, including both current users and potential users, may also differ in their prior knowledge with and about the focal technology and information technology in general. Given that all items of the key UTAUT constructs ask users about their perceptions of and their intentions to use the focal technology, it is quite conceivable that users with varying levels of knowledge about and exposure to information technology in general, as well as the focal technology, may systematically differ in their interpretations of the UTAUT instrument. Thus, we consider the variables pertaining to respondents' engagement with technology as important *within-study* respondent group characteristics that distinguish respondents in a single technology acceptance study.

Prior research has shown that factors such as prior computing experience [29,41], IT competence [40], knowledge, experience and frequency of use of focal technology [41] can have an impact on the invariance of technology acceptance instruments. For example, Doll et al. [29] argue that users with computing experience will evaluate a technology's ease of use and usefulness based on the opinions they formed about technologies in general due to their interaction with various technologies and their features. On the other hand, respondents with no experience with technology will have no frame of reference for comparison, thereby facing difficulty in evaluating the technology's ease of use and usefulness [29]. On the same lines, we posit that key user technology engagement variables may affect the invariance of the UTAUT instrument.

A closer look at the constructs of the UTAUT shows that a respondent's varying degrees and facets of engagement with the technology will play a crucial role in the understanding of the construct. For example, one of the items for the construct "facilitating conditions" asks respondents to what extent they agree with the statement "I have the knowledge necessary to use the system." This item is linked to a respondent's experience of the context. As per [69], understanding of a construct varies with the extent to which the construct is linked to the experience of the context. Consequently, technology engagement variables such as general IT experience or familiarity with the focal technology might influence how a respondent understands this "facilitating condition" scale. However, the UTAUT studies conducted so far have made an implicit assumption that the UTAUT instrument is invariant for respondents on these and other technology engagement variables. In order for a study to generate valid and reliable results that are interpretable, all respondents within the study with varying levels of engagement with the focal technology must interpret the UTAUT instrument in a similar manner. Thus, given that the objective of the UTAUT model is to capture users' technology-related perceptions and ultimately predict the acceptance and use of the focal technology, establishing the UTAUT instrument's invariance with technology engagement variables is paramount.

Of the three invariance studies of the UTAUT scales (see Table 1 above), only the study by Li and Kishore [41] examines the measurement invariance of the UTAUT instrument using grouping variables that pertain to a respondent's engagement with a technology. However, as discussed earlier and shown in Table 1, that study is limited in terms of the invariance tests used. We address these gaps in the extant literature by considering various facets and patterns of a user's engagement with technology. In particular, we consider two facets of respondents' engagement with technology: (a) respondents' prior technology knowledge and (b) respondents' focal technology usage patterns. Furthermore, to develop a deeper and richer understanding of within-study invariance of the UTAUT scales, we consider two types of prior technology knowledge: (a1) respondents' general IT knowledge and (a2) respondents' specific IT knowledge. In addition, to ensure the robustness of our results, we use two operationalizations for respondents' specific IT knowledge (familiarity with the focal technology and experience with the focal technology) as well as two operationalizations for respondents' technology usage patterns (hours spent on the focal technology each time the technology is used and hours spent on the focal technology in the last month).

Fig. 1 illustrates the facets of technology engagement and their operationalizations considered in this study. The variables we study capture a user's experience with the focal technology, which is the current context, as well as his/her experience with any

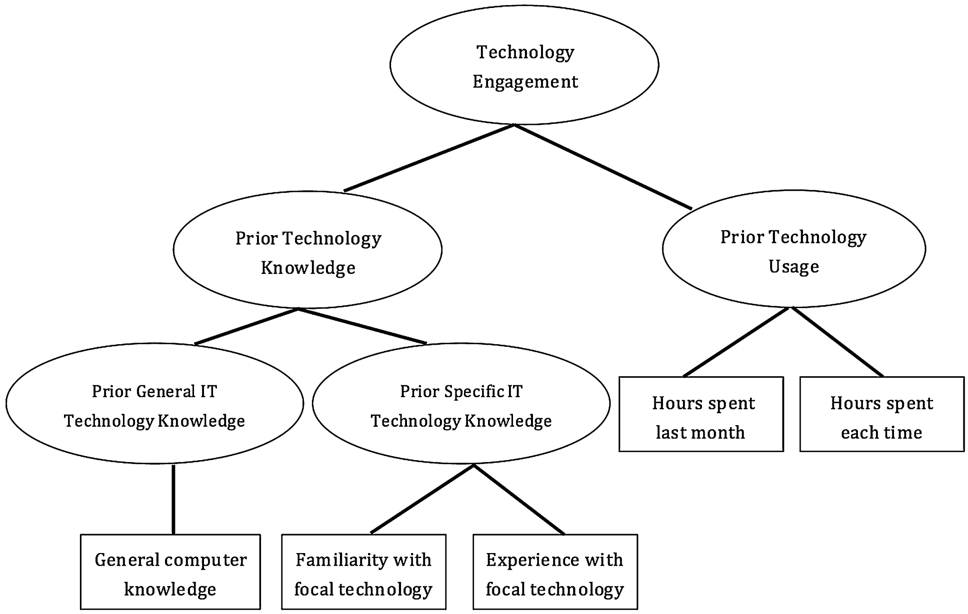

Fig. 1. Technology engagement variables and their operationalizations.

information technology, i.e., the larger context of technology usage. Furthermore, to capture the depth of a respondent's engagement with the focal technology, we also study a user's technology usage pattern. We use several operationalizations for our variables to ensure robustness, and we show that the results we obtain are not merely statistical artifacts. This is especially important for the current study, which seeks to make methodological contributions to the literature, and the robustness of the results obtained using multiple methods (operationalizations) are key to making such contributions. Our approach is also in line with the current trends in the IS field, where studies with additional robustness tests are becoming common to ensure that their results are widely applicable [38,55].

We also include gender as a grouping variable, as most technology acceptance studies include both males and females as respondents in their samples. Although gender has been analyzed in a previous UTAUT invariance study by Kang et al. [39], we include it in the present study to not only preserve the cumulative tradition of gender being used as a key within-study invariance variable but also because repeatability is the hallmark of science, and only Kang et al. [39] have so far performed an invariance analysis of the UTAUT instrument based on gender using the full suite of invariance tests. As mentioned earlier, we perform a full suite of multi-group measurement invariance analyses using the above-mentioned respondent group characteristics in the context of blogs, with a sample of younger respondents who are more likely to use Web 2.0 technologies such as blogs.

4. Measurement invariance hypotheses

In this section, we hypothesize how each respondent group characteristic can impact the invariance properties of the UTAUT scale. As mentioned earlier, we consider a total of six respondent[3] group characteristics (i.e., variables) in our invariance analyses: five variables pertaining to respondents' two technology engagement facets (prior technology knowledge and prior technology usage) and one variable pertaining to their gender. We conduct measurement invariance analyses of the scales for the five key constructs of the UTAUT model: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intention (IU) [50]. We test the fundamental hypothesis of measurement invariance that the five UTAUT scales being tested in this study exhibit measurement invariance with respect to the six respondent group variables considered in this study.

4.1. Respondents' prior IT knowledge

We divide users based on their prior knowledge in the context of technology acceptance. We argue that the extent to which the user possesses prior knowledge with respect to the technology s/he uses might shape his/her frame of reference while evaluating the various constructs of technology acceptance of the UTAUT scale. We classify prior IT knowledge into two types consistent with the literature: general IT knowledge and specific IT knowledge [22,68].

4.1.1. General IT knowledge

General IT knowledge in the technology acceptance context is the general computing knowledge possessed by the user [44]. The findings regarding users' general IT knowledge are rather mixed. Several previous studies find that the level of computing experience has a significant direct effect on the perception of usefulness and ease of use constructs [2,36]. Doll et al. [29] show that while ease-of-use scores are comparable across different groups, usefulness scores are comparable only for some subpopulations (i.e., novice and experienced users) but not for all groups (e.g., users with no prior experience). We also note that individuals with little IT knowledge tend to comply more easily with social influence. Warshaw [65] suggests that individuals are more likely to comply with others' expectations when those referent others have the ability to reward the desired behavior or punish non-behavior. The effect of facilitating conditions is also expected to increase with general IT knowledge as users of technology find multiple avenues for help and support [11,62]. Based on these findings, we conclude that general IT knowledge is an important respondent group characteristic that impacts perceptions about UTAUT model constructs. To test the invariance of the five UTAUT scales with respect to this respondent group characteristic, we hypothesize:

[3] From this point onward, we use the terms respondent and user interchangeably in this study in line with the spirit of the technology acceptance research, in which all respondents are current or potential users of the technology whose acceptance/usage is being investigated.

H1. The five UTAUT scales for PE, EE, SI, FC, and IU are invariant for respondents' general IT knowledge.

4.1.2. Specific IT knowledge

Specific IT knowledge is the knowledge of the local context [44]. In the context of technology acceptance, specific IT knowledge corresponds to a user's knowledge of the focal technology. We further subdivide this respondent group characteristic into familiarity and experience with the focal technology.

4.1.2.1. Familiarity with the focal technology. Users may also have different levels of familiarity pertaining to the focal technology whose adoption/acceptance is being studied. This familiarity about the technology under consideration may also impact their perceptions about the technology and their adoption/acceptance behavior with respect to that technology. In the context of the current paper, the new technology being studied is blogs. Thus, familiarity about blogs is of interest in this paper as a respondent group characteristic from the perspective of invariance analysis across user sub-populations. Specifically, it has been shown that familiarity gained from past behaviors could help shape future intentions [31,33]. One may have a different perception or frame of reference on performance and effort expectancy with different levels of blog knowledge. Agarwal and Prasad [3] show that an individual's opinions are highly influenced by others when he or she owns little knowledge about the particular phenomenon under consideration. It is also reasonable to anticipate that users with little knowledge will need more help and assistance to remove impediments to sustained usage. To test the invariance of the five UTAUT scales with respect to this respondent group characteristic, we hypothesize:

H2. The five UTAUT scales for PE, EE, SI, FC, and IU are invariant for respondents' familiarity with the focal technology.

4.1.2.2. Experience with the focal technology. Users may vary widely in their prior experience with the focal technology under question. Several studies have found prior experience to be an important determinant of behaviors [4,7,10]. This is partly because past experience may make low probability events more salient and ensure that they are accounted for in the formation of intentions [4]. Experience can also make knowledge more accessible in memory [32]. This suggests that experience may have an impact on individual frames of reference with respect to UTAUT scales. Several previous studies have also suggested that a user's experience could have an influence on their frame of reference [29]. Previous research with respect to TAM has discussed how users' perception of the two TAM constructs of ease-of-use and usefulness vary with the individual's level of experience [2]. Furthermore, Igbaria et al. [36] have found that different prior experiences had a direct effect on perception of usefulness and ease of use. Their findings suggest that users' previous experience may affect their frame of reference for evaluating "usefulness" and "ease of use" in TAM. It is easy to understand that users without any experience with blogs may have difficulties forming ideas and opinions about, for example, usefulness and effort expectancy with respect to this technology. On the other hand, experienced users could have a better cognizance of blogs based on their prior experience. Their standards for evaluating the performance and effort expectancy and for forming perceptions with respect to other crucial adoption and usage variables may be quite different from those users who have no prior experience with the focal technology. Taylor and Todd [56] also suggest that an individual's opinions are relatively ill-informed in the early stages of experiences. Inexperienced users are more inclined to be impacted by social influences. As a result, it is also more likely that inexperienced users attach more importance to receiving help and assistance from others in the domain of facilitating conditions. Therefore, prior experience with the focal technology is an important respondent group characteristic in the context of technology acceptance. To test the invariance of the five UTAUT scales with respect to this respondent group characteristic, we hypothesize:

H3. The five UTAUT scales for PE, EE, SI, FC, and IU are invariant for respondents' experience with the focal technology.

4.2. Respondents' technology usage patterns

Users can also vary in the way they use the system. A user with high usage of a technology is expected to have explored a larger functionality of that technology. Thus, such users may also develop a higher degree of knowledge about that technology and are expected to have a frame of reference that is based on more intensive experience. On the other hand, users with low usage of a technology may have explored a more limited functionality, and their opinions about this new technology may, therefore, be substantially different than those with high usage. Therefore, we find that the user's technology usage pattern is another important respondent group characteristic in the context of our study. To ensure robustness in our results, we use two operationalizations for users' technology usage patterns: (1) hours spent on the focal technology in the last month and (2) hours spent on the focal technology each time the technology is used. To test the invariance of the five UTAUT scales with respect to these two respondent group characteristics, we hypothesize:

H4. The five UTAUT scales for PE, EE, SI, FC, and IU are invariant for respondents' hours spent on the focal technology last month.

H5. The five UTAUT scales for PE, EE, SI, FC, and IU are invariant for respondents' hours spent on the focal technology each time the technology is used.

4.3. Respondents' gender

Users' gender has been widely studied as a main demographic variable in the area of IT adoption, and several studies provide evidence of gender differences in this area. Findings indicate that males have significantly higher positive attitudes toward computing than females [23,35,66]. Furthermore, it has been suggested that even though attitudes are statistically significant across gender differences, they are quite small in the absolute sense [23]. Eagly [30] has also shown that gender differences could affect one's orientation or frame of reference toward phenomena considered in social sciences. It was also found that men tend to be highly task-oriented and that women are more communally oriented [30,47]. Due to these known gender differences in the technology adoption area, Doll et al. [29] use gender as one of the variables for conducting their multi-group invariance analysis using Davis's perceived usefulness and perceived ease-of-use instruments. They argue that user's gender could play an important role in determining one's frame of reference for evaluating usefulness and ease of use, which results in nonequivalent scales that may not be comparable across these two sub-groups. In their invariance analysis, they find that the perceived usefulness instrument is not invariant across user's gender; however, this is not the case for the ease-of-use instrument. Particularly, Venkatesh et al. [62] suggests that effort expectancy is more salient for women than for men. Women are also more sensitive to others' opinions and, therefore, social influence would also be more salient for them [46,61]. It is also likely that women have a higher perception of assistance and support. Based on these findings, we conclude that the user's gender is an important respondent group characteristic that impacts perceptions about constructs similar to the UTAUT constructs. To test the invariance of the five UTAUT scales with respect to this respondent group characteristic, we hypothesize:

H6. The five UTAUT scales for PE, EE, SI, FC, and IU are invariant for respondents' gender.

5. Research methodology

5.1. Methodology for testing measurement invariance

Measurement invariance should be established before researchers compare the results of survey items. Establishing measurement invariance shows that the survey respondents belonging to different groups have ascribed the same meaning to the survey items [19]. Measurement invariance can be established by performing Multi-Group Confirmatory Factor Analysis (MGCFA). By performing an MGCFA, the measurement model of the survey instrument is compared across two or more groups. Because we are testing the measurement invariance of the UTAUT model, the measurement model in our case is a simple model with five latent constructs, i.e., five key UTAUT model constructs that are correlated with each other. There are various degrees of stringency in the process of establishing measurement invariance. For example, invariance could be established on a number of parameters such as factor loadings of indicator variables, intercepts of indicator variables, residual variances of indicator variables, means of the latent variables and with covariances among latent variables. To establish that there are no differences between the groups in the parameter of interest, the parameter is constrained to be equal when establishing the measurement model. This model is the constrained model. A difference in χ^2 test is then performed between the χ^2 values of the unconstrained and constrained models. These two models are estimated separately, and the χ^2 is computed by fitting the model with the pooled sample of the all the groups. A non-significant χ^2 test indicates that the parameters are the same across the groups and that measurement invariance is evident.

We follow the comprehensive and state-of-art methodology for measurement invariance testing provided by Cheung [18] and Cheung and Lau [19], and we conduct the full suite of measurement invariance tests (summarized below) on the first-order UTAUT constructs in the sequence illustrated in these papers. We only conduct tests with first-order constructs, as all constructs in the UTAUT model are first-order constructs. It should be noted that Cheung's [18] and Cheung and Lau's [19] measurement invariance testing methodology papers were published in "Organizational Research Methods," a highly regarded journal in the organizational research field that publishes rigorous research on the latest advancements in research methods. In the following paragraphs, we briefly discuss the various tests of measurement invariance and their related hypotheses, as proposed by Cheung [18] and Cheung and Lau [19].

5.1.1. Configural invariance

Configural invariance is established when the number of constructs and the respective indicator variables are the same across different groups of interest [18]. Lack of configural invariance renders cross-group comparisons of construct means meaningless because the constructs have different configuration across the groups. Lack of configural invariance also implies that the constructs have different factor structures across groups [58]. The configural invariance has to be established for all other invariances to be tested.

5.1.2. Metric invariance

Metric invariance is established when the factor loadings (λ_{ij}) of indicator variables on the latent constructs are equal across groups. The hypothesis for metric invariance is $\lambda_{ij}{}^{(1)} = \lambda_{ij}{}^{(2)} = \ldots = \lambda_{ij}{}^{(g)}$ for all i items and j first-order constructs, where g is the group number [18]. Because the factor loadings indicate the strength of the relationship between the indicator variables and the latent constructs, metric invariance shows that the unit of measurement for each construct is identical across groups [51]. Bollen [12] suggests that the next step is to test whether those measures related to a set of underlying constructs are perceived similarly across multiple groups.

5.1.3. Uniqueness invariance

Uniqueness invariance is established when the variances (ε_i) in the measurement error of each indicator variable are equal across groups. The hypothesis for uniqueness invariance is $\varepsilon_i{}^{(1)} = \varepsilon_i{}^{(2)} = \ldots = \varepsilon_i{}^{(g)}$ for all i items, where g is the group number [18]. Uniqueness invariance shows that the indicator variables measure the construct with the same degree of measurement error across the groups [18]. In other words, uniqueness invariance shows that the items are equally reliable across the groups [25].

5.1.4. Invariance in construct variance

Invariance in construct variance is established when the variances (ψ_j) among constructs are equal across groups. The hypothesis for invariance in construct variance is $\psi_j{}^{(1)} = \psi_j{}^{(2)} = \ldots = \psi_j{}^{(g)}$ for all j first-order constructs, where g is the group number [18]. This type of invariance is needed for the comparisons of construct covariances across groups to be meaningful [18].

5.1.5. Invariance in construct covariance

Invariance in construct covariance ($\psi_{jj'}$) is established when the covariances among constructs are equal across groups. The hypothesis for invariance in construct covariance is $\psi_{jj'}{}^{(1)\prime} = \psi_{jj'}{}^{(2)\prime} = \ldots = \psi_{jj'}{}^{(g)\prime}$ for all j first-order constructs, where g is the group number and $j \neq j'$ [18]. Invariance in construct covariance shows that the strength of the relationship among the constructs is identical across groups [18].

5.1.6. Scalar invariance

Scalar invariance is established when the intercepts (τ_i) of indicator variables on the latent constructs are equal across groups. The hypothesis for scalar invariance is $\tau_i{}^{(1)} = \tau_i{}^{(2)} = \ldots = \tau_i{}^{(g)}$ for all i items, where g is the group number [18]. Scalar invariance shows that the amount of scores in one group is same as that in another [57]. Scalar invariance means the origin of the scales is same across the subgroups [51].

5.1.7. Invariance in latent means

Invariance in latent means is established when the means (α_j) of the first order constructs are equal across groups. The hypothesis for invariance in latent means is $\alpha_j{}^{(1)} = \alpha_j{}^{(2)} = \ldots = \alpha_j{}^{(g)}$ for all j constructs, where g is the group number [18]. This type of invariance can be established only when the metric and scalar invariance is established because it is meaningless to compare the means of constructs that have different units of measurement and origin [18]. Sometimes researchers may establish partial metric or partial scalar invariance, where the non-invariant factor loadings or intercepts are not constrained to be equal while estimating the measurement model across two groups [18]. This implies a recalibration of scales, after which the comparison of latent constructs can be performed [18]. However, after establishing partial metric or scalar invariance, a construct needs to have at least two of its indicators be invariant for the comparison of the latent means to be meaningful [52].

5.2. Data collection and sample

To perform the invariance analysis presented above, a survey was conducted of freshmen students in the business school of a large university in Hong Kong. Students are a very appropriate population for this study for two reasons. First, social networking tools such as blogs are a recent phenomenon, and younger generations are the main users of such tools. An analysis of over 600 million social networking profiles and 2 billion web documents that reference people indicates that the largest subgroup, comprising 37% of all users, are age 25 or under.[4] Second, students are also among the main users of information technologies in general, as they use all types of new information technologies, including learning technologies such as Blackboard systems, communication technologies such as smart phones and e-mail systems, and a variety of social networking technologies such as Facebook and MySpace. Thus, students are a very important demographic from the perspective of technology acceptance of social networking tools such as blogs. For these reasons, students are deemed to be an appropriate sample to test the invariance properties of the UTAUT constructs outlined above.

Although blogs have been popular since the late 1990s, these technologies are still in vogue, despite the emergence of social networking sites such as Facebook. A study by Nielson shows that the number of blogs created is on the rise, with 181 million blogs posted in 2011 compared to just 36 million in 2006 [48]. The study also shows that half the bloggers are age between 18 and 34 [48]. The statistics page of WordPress, the most popular blogging tool, shows that the number of websites that integrate WordPress in their websites is steadily on the rise [13]. Thus, given the popularity and sustained usage of blogs among internet users, we used them as a technology context for this study. Moreover, at the time when these data, were collected blogs were an emerging technology.

Our study investigated the UTAUT invariance in the context of blogs. While a blog is one type of technology, there are other social network websites such as Facebook that are growing in popularity for which UTAUT invariance needs to be established. While it is important to test UTAUT invariance for the type of technology, it is an across-study variable, and hence, we restricted our study to a single technology context. As highlighted in the literature survey, there are few technology acceptance studies that analyze across-study variables such as type of technology/application [27,29]. For example, Kang et al. [39] tested the UTAUT invariance across two technologies, namely, internet banking and MP3 players, and found that the measurement model is invariant only on the configural, factor variance and factor covariance criteria.

The students were asked to complete a survey after a brief introductory information systems laboratory session. While the survey was entirely voluntary, it produced a high response rate, with 265 completed surveys out of 280 total surveys issued. We cleaned the dataset for missing data and incomplete responses. This gave us 250 data points to perform the invariance analysis. Table 2 shows the demographic background of the survey respondents.

In the survey, we included a brief introductory message about weblogs, and we mentioned that the survey questions are about weblogs (see Appendix A). The introductory message also provided clarification on what we mean by the use of weblogs. Although "use of weblog" can denote several activities, such as using weblogs for creating content, establishing a social network with other blog users, or reading content created by other users, we are interested in weblog use that pertains to creating content and establishing social relationships. These are the activities that require prior technology engagement, and they can affect the invariance of the UTAUT scale.

Table 2
Background of respondents.

Gender	Male: 87 (34.8%)
	Female: 163 (65.2%)
Age	Below 18: 5 (2%)
	18–22: 245 (98%)
General IT knowledge	Very little: 45 (18%)
	Fair: 163 (65.2%)
	Good: 40 (16.0%)
	Expert: 2 (0.8%)
Particular blog knowledge (familiarity with blog)	Not at all: 89 (35.6%)
	A little bit: 94 (37.6%)
	Familiar: 49 (19.6%)
	Very familiar: 18 (7.2%)
Experience with blog	Never: 106 (42.4%)
	Less than 1 year: 6 (24%)
	1–2 years: 60 (24%)
	3–4 years: 19 (7.6%)
	More than 4 years: 5 (2%)
Frequency of using blog	Seldom: 121 (48.4%)
	At least once a month: 14 (5.6%)
	At least once a week: 46 (18.4%)
	Once a day: 69 (27.6%)

The first part of the survey collected demographic data and respondents' usage patterns with respect to blogs. The second part consisted of 19 statements asking respondents' opinions about blog usage on a seven point Likert scale, where 1 represented strongly disagree and 7 represented strongly agree. These 19 statements included four items for each of the four constructs, including performance expectancy, effort expectancy, social influence and facilitating conditions, and three items for behavioral intention, which were directly adopted from Venkatesh et al. [62]. The items of the UTAUT we used are shown in Appendix B.

Data collected on these six respondent group characteristics were divided into two sub-groups for each variable. In the gender respondent group characteristic, there are 87 male responses and 163 female responses. In the respondent group characteristic of general IT knowledge, two groups are classified as "very little to fair," with 208 responses, and "good to expert," with 42 responses. We classified "very little to fair" in one group because it represents "low general IT knowledge" and "good to expert" in another group because it represents "high general IT knowledge". The specific IT knowledge respondent group characteristic was sub-divided into familiarity and experience with the focal technology (in our case, blogs). In the familiarity with focal technology respondent group characteristic, two groups are classified as "not at all and a little bit familiar," with 183 responses, and "familiar to very familiar," with 67 responses. We classified "not at all and a little bit familiar" in one group because it represents low familiarity with focal technology and "familiar to very familiar" in another group because it represents high familiarity with focal technology. In the experience with focal technology respondent group characteristic, two groups are classified as "never," with 106 responses, and "less than 1 year to more than 4 years," with 144 responses. Because this experience variable measures specific IT knowledge with respect to the focal technology, we wanted a group that knows nothing about the focal technology. Thus, we grouped "never" into one group representing "no experience" with the focal technology and "less than 1 year to more than 4 years" into another group representing at least some experience with the focal technology.

[4] http://www.fastcompany.com/blog/jay-bhatti/its-all-about-search/age-distribution-people-web.

Table 3
Two subgroups under each respondent group characteristic.

Respondent group characteristics		Measures	Subgroups
User's gender		Gender	Group 1: Male: 87 (34.8%) Group 2: Female: 163 (65.2%)
User's prior IT knowledge	General IT knowledge	General computing knowledge	Group 1: Very little to Fair: 208 (83.2%) Group 2: Good to Expert: 42 (16.8%)
	Specific IT knowledge	Familiarity with blog	Group 1: Not at all familiar or a little bit familiar: 183 (73.2%) Group 2: Familiar or very familiar: 67 (28.8%)
		Years of experience with blog	Group 1: Never: 106 (42.4%) Group 2: Less than 1 year, 1–2 years, 3–4 years, more than 4 years: 144 (57.6%)
User's technology usage pattern		Total hours spent on a blog in the last month	Group 1: Below 3 h: 141 (56.4%) Group 2: Above 3 h: 109 (43.6%)
		Number of hours spent on a blog each time	Group 1: Below 0.5 h: 156 (62.4%) Group 2: Above 0.5 h: 94 (37.6%)

We use two measures to operationalize user's technology usage pattern: total hours spent on blogs each month and number of hours spent on a blog each time. For user's technology usage pattern measured with total hours spent on a blog last month, we use the mean value on this variable as the division point. This results in 141 responses from the "low usage" group and 109 responses from the "high usage" group. Similarly, for the user's technology usage pattern measured with the number of hours spent on a blog each time, we use the mean value on this variable as the division point. This results in 156 responses from the "low usage" group and 94 responses from the "high usage" group. The detailed classification of the groups is provided in Table 3.

6. Data analyses

In this section, we present the steps used to analyze the measurement invariance of the UTAUT instrument. First, we check for the internal consistency, dimensionality, convergent, and divergent validity of the constructs. Second, using confirmatory factor analysis, we develop a baseline measurement model with the UTAUT items tested by Venkatesh et al. [62]. We use this model for all the invariance analyses in this study. Third, we perform measurement invariance analysis for each respondent group characteristic.

6.1. Internal consistency of the constructs

To check the internal consistency of the constructs, we used the following measures: Cronbach's alpha (α), composite reliability (CR) and the goodness-of-fit statistics. A Cronbach's alpha of 0.7 or greater and a composite reliability value of 0.7 or greater are all commonly agreed upon indicators of internal consistency. Three goodness-of-fit indices GFI, NFI and CFI were used to assess the internal consistency of the constructs. A value of 0.90 or higher on these goodness-of-fit indices indicates good model fit [5,37,40,57]. To perform this analysis, all the first order constructs of the UTAUT model were loaded with their respective indicators adopted from Venkatesh et al. [62]. The constructs performance expectancy, effort expectancy, social influence and facilitating conditions were loaded with four items each, and the intention to use construct was loaded with 3 items. The five constructs were estimated individually by Confirmatory Factor Analysis using IBM® SPSS® AMOS 21.0.0. Table 4 presents the values of the Cronbach's alpha, composite reliability and the goodness-of-fit indices for the five constructs of the UTAUT model. The threshold condition was satisfied for all constructs except the performance expectancy construct. Because it is inappropriate to conduct invariance studies using constructs with low item loadings, two items, PE1 and PE2, that exhibited low factor loadings were removed from this construct. This removal improved the internal consistency (α = 0.73, CR = 0.78) to acceptable levels. According to Steenkamp and Baumgartner [52], a minimum of two items need to be invariant to make a meaningful comparison of the latent construct means across the groups. Thus, given that we still have PE3 and PE4, removing the two items PE1 and PE2 does not affect the invariance analysis. Although we dropped the two items PE1 and PE2, the other two items, PE3 and PE4 (please refer to Appendix B) do adequately measure the performance expectancy of the respondent. Moreover, previous UTAUT invariance studies have been conducted with reduced items for the constructs [37]. Overall, our findings indicate strong support for the internal consistency of all the constructs in the study.

6.2. Dimensionality, convergent, and discriminant validity

To establish the dimensionality, convergent and discriminant validity, three models are established, and each is compared with the others for significantly better fit. Model 1 hypothesizes that the variance among all the items in the constructs is explained by a one-dimensional latent factor. Model 2 hypothesizes that the items form five uncorrelated first order latent factors: performance expectancy, effort expectancy, social influence, facilitating conditions and intention to use. Model 3 hypothesizes that these five first-order latent factors are freely correlated. Subsequently, Model 1 was set up with the five latent constructs with all the indicators, as mentioned by Venkatesh et al. [62]. For the performance expectancy construct, we did not include the two items that were removed in the internal consistency analysis. We set each cross-construct correlation among the five constructs to unity, thereby

Table 4
Internal consistency of measures.

Construct	No. of items	Cronbach's alpha	Composite reliability	GFI	NFI	CFI
Performance expectancy	4	0.60	0.63	1.00	0.99	1.00
Effort expectancy	4	0.75	0.73	1.00	1.00	1.00
Social influence	4	0.74	0.71	1.00	0.99	1.00
Facilitating conditions	4	0.77	0.77	0.99	0.98	0.98
Intention to use	3	0.86	0.83	1.00	1.00	1.00

signifying that all the items load onto one factor. Model 2 was set up by making the correlations between these latent constructs zero, signifying that the measurement model consists of five uncorrelated constructs. Model 3 was set up by freely estimating the correlations between the constructs, thereby signifying the distinctiveness of the constructs. Model 2 was not estimated because it was an under-identified model. Hence, we only compare models 1 and 3. A comparison of Model 3 ($\chi^2 = 272.22$, $df = 109$) with Model 1 shows that Model 1 ($\chi^2 = 408.00$, $df = 119$) has a superior fit ($\Delta\chi^2 = 135.78$, $\Delta df = 10$; $p < 0.001$) in the nested χ^2 difference test. This indicates that the measurement model is multi-dimensional, i.e., it consists of five first-order latent factors. All factor loadings of Model 3 are above 0.5 and statistically significant ($p < 0.001$), which is evidence of convergent validity. Except for the correlation between effort expectancy and facilitating conditions, which is marginal at 0.91, all the other cross-construct correlations between the constructs are below the threshold of 0.90 [8], which shows that the baseline measurement model adequately discriminates among the five constructs. Thus, our analysis shows strong support for multi-dimensionality, convergent validity and divergent validity.

6.3. Model fit of the baseline measurement model

Having established the reliability and validity of the constructs, the next step is to finalize the baseline measurement model to be used for the invariance analysis. Several goodness-of-fit indices can be used to assess the model fit of the baseline measurement model in a confirmatory factor analysis. Typically, a positive χ^2 test with a significance level of 0.05 indicates model fit [5,37,40,57]. Because the χ^2 test is affected by the sample size, we use the ratio of the χ^2 value to the degrees of freedom (*df*), with χ^2/df values of less than 3 indicating adequate model fit [5,37,40,57]. We also use other fit indices, such as the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Incremental Fit Index (IFI) and Root Mean Square Error Approximation (RMSEA), with values of 0.90 or greater on IFI, TLI and CFI and of 0.08 or lower on the RMSEA indicating good model fit [5,37,40,57].

Model 3 (discussed in Section 5.2) is also our baseline measurement model because it contains all five major constructs freely correlated with each other. Although the model fit ($\chi^2 = 272.22$, $df = 109$, $p < 0.001$, $\chi^2/df = 2.50$, RMSEA = 0.08, IFI = 0.90, TLI = 0.88, CFI = 0.90) was sufficient, we wanted to further improve it. We removed item SI3, which was highly correlated with other constructs in the model. The removal of SI3 improved the model fit ($\chi^2 = 208.57$, $df = 94$, $p < 0.001$, $\chi^2/df = 2.22$, RMSEA = 0.07, IFI = 0.92, TLI = 0.90, CFI = 0.92) to better thresholds on the goodness-of-fit indices. To further improve the model fit, we inspected the modification indices and correlated the error variances of FC1 and FC2, FC2 and FC3 and FC3 and FC4. The final model consisted of the five main constructs of the UTAUT freely correlated with each other by excluding items PEI, PE2 and SI3 and by correlating the error terms [14], as mentioned previously ($\chi^2 = 165.89$, $df = 91$, $p < 0.001$, $\chi^2/df = 1.82$, RMSEA = 0.06, IFI = 0.95, TLI = 0.93, CFI = 0.95). Table 5 lists the items, their standardized factor loadings and the model fit of the final baseline measurement model. All factor loadings of Model 3 are above 0.5 and are statistically significant ($p < 0.001$), indicating convergent validity. The goodness-of-fit indices were all above the thresholds, thereby indicating model fit.

Table 5
Confirmatory factor analysis of the baseline measurement model.

Construct	Measures	Standardized factor loading
Performance expectancy	PE3	1.02[a,***]
	PE4	0.56***
Effort expectancy	EE1	0.65***
	EE2	0.76***
	EE3	0.63***
	EE4	0.57***
Social influence	SI1	0.70***
	SI2	0.55***
	SI3	0.67***
Facilitating conditions	FC1	0.53***
	FC2	0.51***
	FC3	0.71***
	FC4	0.81***
Intention to use	IU1	0.76***
	IU2	0.88***
	IU3	0.83***

Goodness-of-fit statistics for the baseline measurement model.
$\chi^2 = 165.89$, $df = 91$, $p < 0.001$, $\chi^2/df = 1.82$, RMSEA = 0.06, IFI = 0.95, TLI = 0.93, CFI = 0.95.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
[a] Standardized factor loadings can be greater than 1 if the factors are correlated, in which case the factor loadings are regression weights, not correlations. Because a regression weight can be greater than 1, factor loadings can also be greater than 1 in magnitude (Jöreskog, K. G., 1999).
Jöreskog, K.G. (1999). "How large can a standardized coefficient be?" *Retrieved February*, 2, 2005.

6.4. Measurement invariance analyses

The final measurement baseline model was used to perform the invariance analysis for the various respondent group characteristics. We used the sequence of invariance analysis (discussed earlier) suggested by Cheung [18]. For each respondent group characteristic, a series of nested χ^2 tests were performed between the constrained and unconstrained models to assess the invariance at various levels of equivalence. A significant increase in the χ^2 for the constrained model means the invariance hypothesis is rejected. If the metric or scalar invariance was rejected, we identify the non-invariant items by factor-ratio tests [20] and the list-and-delete methodology [19]. Finally, we establish whether the constructs are comparable for each respondent group characteristic. A comparison of the latent means of the constructs is performed if the measurement model is sufficiently equivalent to make such comparisons unambiguous. In addition to the χ^2 test, we assessed model fit using the goodness-of-fit statistics χ^2/df, RMSEA, IFI, TLI and CFI.

6.4.1. Sequence of measurement invariance analysis

Although the scholars in the Structural Equation Modeling (SEM) discipline have proposed various sequences of tests for measurement invariance (e.g., [18,17,59]), the sequence depends on the type of empirical questions under consideration in the study [19]. For the purpose of this paper, we follow the sequence proposed by Cheung [18]. Once configural invariance is established, the other tests of measurement invariance are studied at three different levels. Level 1 is the configural invariance model, and level 2 is the metric invariance model. This model is established by proving that there is no significant difference between the model fit of a model obtained by constraining the factor loadings to be equal across groups and the model fit of the level 1 configural invariance model. If the metric invariant model is significantly different from the level 1 model, identifying the non-invariant factor loadings and removing the equivalency constraints on them across groups results in a partial metric equivalence model. If this partial metric equivalence model is not significantly different from the configural invariance model, then it is set at level 2. For items that have non-invariant factor loadings across groups, their intercepts are also assumed to be non-invariant, and hence, equality constraints are not set when estimating the scalar invariance model [21]. The models of invariance in residual (uniqueness), construct covariance,

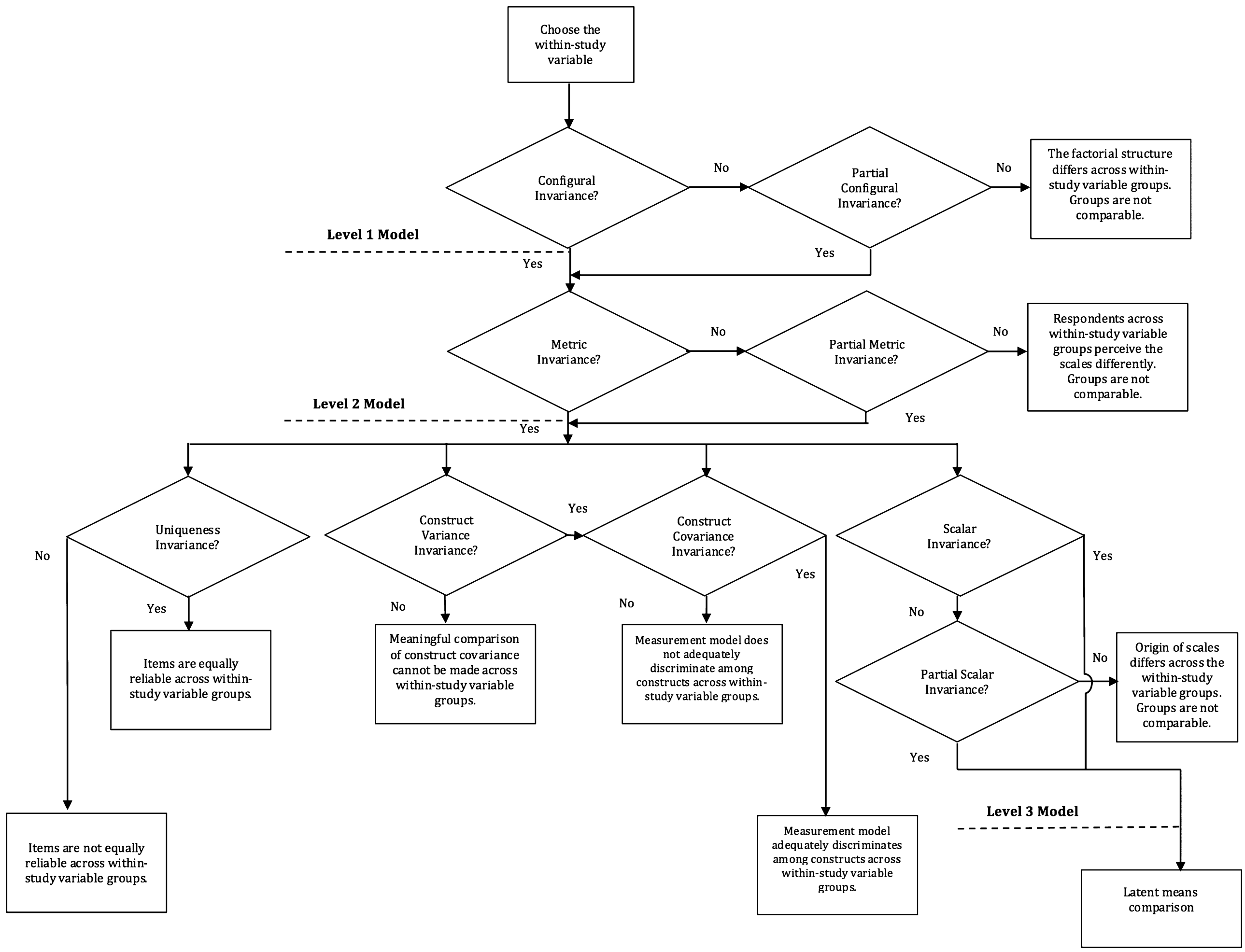

Fig. 2. Invariance analysis sequence.
Adapted from the studies: Delgado-Ballester [27]; Cheung [17]; Lai and Li [17]; Steenkamp and Baumgartner [28]; Vandenberg and Lance [66].

construct variance and intercepts (scalar) are all compared with the level 2 model. If the scalar invariance is rejected, identifying the non-invariant intercepts and removing the equivalency constraints on them across groups results in a partial scalar equivalence model. If this partial scalar equivalence model is not significantly different from the model at level 2, it is set at level 3. To compare the latent means, in the level 3 model, the latent means of one group is set to zero and that of the other group is set free to vary. This new model is estimated. The estimated factor mean of the group whose means were set to vary is the difference between the latent means across the groups. Fig. 2 illustrates the sequence of the invariance analysis.

6.4.2. Establishing partial invariance

When the metric or the scalar invariance tests are rejected, we try to establish a partial metric or partial scalar invariant model. Identifying non-equivalent parameters and removing their equality constraints across groups results in the partially invariant model. Establishing the invariant set of indicators can identify the non-equivalent parameters. To achieve this, we employ the factor-ratio test proposed by Cheung and Rensvold [20]. For each indicator used as a referent, the parameters of interest of the other items (called the argument) are tested for equality on an individual basis [18]. This process is repeated for every item to obtain referent-argument pairs that fail the invariance tests [18]. Using these pairs, we identify the invariant sets by using the list-and-delete methodology [19]. Typically, when more than one invariant sets are identified, the choice of the invariant set of items to be used in the model should be theoretically motivated [20].

7. Results from invariance analyses

In this section, to demonstrate how we performed the invariance analysis, we discuss the results for two technology engagement variables: general IT knowledge and experience with the focal technology. We chose these two variables because their analyses required the full range of decisions needed to perform the invariance analysis, and hence, they would serve as a good model. In the following section, we summarize the invariance analyses of these two variables. Appendix C provides the details of the other variables not explained in this section.

7.1. General IT knowledge

The results in Table 6 show that configural invariance was supported for the baseline measurement model (Model 1). Next, the full metric invariance model (Model 2) was established. This model was nested with Model 1. Because the χ^2 of the full metric invariance model was significantly greater ($\Delta\chi^2 = 20.48$, $\Delta df = 11$, $p < 0.05$) than the configural model, metric invariance was rejected. Then, we applied the factor-ratio tests [20] and the list-and-delete methodology [19] to identify the non-invariant items. The factor loading of item EE1 was found to be non-invariant across groups. A partial metric invariance model

Table 6
Invariance analysis by general IT knowledge.

Model	Test of equivalence	Unconstrained vs. constrained models	df	χ^2	χ^2/df	RMSEA	IFI	TLI	CFI	Δdf	$\Delta\chi^2$	p-value
1	Configural invariance		182	322.02	1.77	0.06	0.92	0.88	0.91			
2	Full metric invariance	1 vs. 2	193	342.50	1.78	0.06	0.91	0.88	0.91	11	20.48*	0.04
3	Partial metric invariance	1 vs. 3	192	336.24	1.75	0.06	0.91	0.89	0.91	10	14.22	0.16
4	Uniqueness invariance	3 vs. 4	210	372.20	1.77	0.06	0.90	0.88	0.90	18	35.96***	0.01
5	Invariance in construct variance	3 vs. 5	197	342.11	1.74	0.05	0.91	0.89	0.91	5	5.87	0.32
6	Invariance in construct covariance	3 vs. 6	197	344.75	1.75	0.06	0.91	0.89	0.91	5	8.52	0.13
7	Full scalar invariance	3 vs. 7	207	360.54	1.74	0.06	0.91	0.89	0.90	15	24.31	0.06

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

(Model 3) was established by constraining all factor loadings except item EE1. The partial metric invariance model fit the data well, and the χ^2 difference between this model and the configural model was not significant ($\Delta\chi^2 = 20.48$, $\Delta df = 11$, $p > 0.05$). This partial metric invariance model was then used as a baseline model for comparing the other invariance models. Next, the uniqueness invariance model (Model 4) was established. This model was nested with Model 3. Because the χ^2 of the uniqueness invariance model was significantly greater ($\Delta\chi^2 = 35.96$, $\Delta df = 18$, $p < 0.001$) than that of the partial metric invariance model, uniqueness invariance was rejected. Next, the invariance in the construct variance model (Model 5) was established. This model was nested with Model 3. The fit of this model was acceptable, and the model did not differ significantly from Model 3. Next, the invariance in construct covariance model (Model 6) was established. This model was nested with Model 3. The fit of this model was acceptable, and the model did not differ significantly from Model 3. Finally, the full scalar invariance model (Model 7) was established. This model was nested with Model 3. The fit of this model was acceptable, and the model did not differ significantly from Model 3. Because we obtained partial metric equivalence with all constructs having at least two items invariant, and because we established the full scalar invariance, the latent means can be compared across the users with low and high general IT knowledge.

To compare the latent means, in Model 7, the latent means of the high computer knowledge group was set to zero, and that of the low computer knowledge group was set free to vary. This new model was estimated. The estimated factor mean of the low computer knowledge group is the difference between the latent means of the two groups on the five main constructs of the UTAUT model. Table 7 shows the estimated difference in latent means and the model fit of this new model. Our results show that the model fit was acceptable. The latent mean of the effort expectancy construct was significantly lower in the low computer knowledge group. There was no significant difference between the latent means of the other four UTAUT constructs across the two groups.

7.2. Experience with focal technology

The results in Table 8 show that configural invariance was supported for the baseline measurement model (Model 1). Next, the full metric invariance model (Model 2) was established. This model was nested with Model 1. Because the χ^2 of the full metric invariance model was significantly greater ($\Delta\chi^2 = 30.68$, $\Delta df = 11$, $p < 0.001$) than that of the configural model, metric invariance was rejected. Then, we applied the factor-ratio tests and the list-and-delete methodology to identify the non-invariant items. The invariant sets of items for the effort

Table 7
Differences between latent means of high and low general IT knowledge.

Construct	Difference in latent means	Standard error	Critical ratio	p-value
Performance expectancy	0.11	0.19	0.57	0.57
Effort expectancy	−0.51***	0.16	−3.20	0.00
Social influence	−0.08	0.15	−0.50	0.62
Facilitating conditions	−0.04	0.10	−0.42	0.67
Intention to use	−0.10	0.15	−0.69	0.49

Goodness-of-fit statistics for the latent means comparison model.
$\chi^2 = 346.37$, $df = 202$, $p < 0.001$, $\chi^2/df = 1.72$, RMSEA = 0.05, IFI = 0.91, TLI = 0.89, CFI = 0.91.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 8
Invariance analysis by specific IT knowledge – years of experience with focal technology.

Model	Test of equivalence	Unconstrained vs. constrained models	df	χ^2	χ^2/df	RMSEA	IFI	TLI	CFI	Δdf	$\Delta\chi^2$	p-value
1	Configural invariance		182	332.24	1.83	0.06	0.90	0.86	0.89			
2	Full metric invariance	1 vs. 2	193	362.92	1.88	0.06	0.88	0.85	0.88	11	30.68***	0.00
3	Partial metric invariance	1 vs. 3	190	343.60	1.81	0.06	0.90	0.86	0.89	8	11.36	0.18
4	Uniqueness invariance	3 vs. 4	206	362.95	1.76	0.06	0.89	0.87	0.89	16	19.35	0.25
5	Invariance in construct variance	3 vs. 5	195	351.17	1.80	0.06	0.89	0.86	0.89	5	7.57	0.18
6	Invariance in construct covariance	3 vs. 6	200	372.71	1.86	0.06	0.88	0.85	0.88	10	29.12***	0.00
7	Full scalar invariance	3 vs. 7	203	427.09	2.10	0.07	0.85	0.81	0.84	13	83.49***	0.00
8	Partial scalar invariance	3 vs. 8	192	344.43	1.79	0.06	0.90	0.87	0.89	2	0.83	0.66

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

expectancy construct were EE1, EE2 and EE4. For the facilitating conditions construct, two invariant sets (FC1, FC2, FC4) and (FC1, FC3, FC4) were identified. Similarly, for the social influence construct, two invariant sets (SI1 and SI4) and (SI2 and SI4) were identified. Typically, when more than one invariant set is identified, the choice of the invariant set of items to be used in the model should be theoretically motivated [20]. However, because the objective of this study is to check the robustness of the overall measurement model, we are not interested in analyzing the theoretical importance of each item. Therefore, we chose the item sets (EE1, EE2, EE4), (SI1, SI4), and (FC1, FC3, FC4) that gave us the lowest difference in χ^2 value in comparison with the configural model. A partial metric invariance model (Model 3) was established by constraining all factor loadings except items EE3, FC2 and SI2. The partial metric invariance model fit the data well, and the χ^2 difference between this model (Model 3) and the configural model (Model 1) was not significant ($\Delta\chi^2$ = 11.36, Δdf = 8, $p > 0.05$). This partial metric invariance model was then used as a baseline model for comparing the other invariance models. Next, the uniqueness invariance model (Model 4) was established. This model was nested with Model 3. The fit of this model was acceptable, and the model did not differ significantly from Model 3. Next, the invariance in construct variance model (Model 5) was established. This model was nested with Model 3. The fit of this model was acceptable, and the model did not differ significantly from Model 3. Next, the invariance in construct covariance model (Model 6) was established. This model was nested with Model 3. Because the χ^2 of the construct covariance model was significantly greater ($\Delta\chi^2$ = 29.12, Δdf = 10, $p < 0.001$) than that of the partial metric invariance model, the invariance in construct covariance was rejected. Finally, the full scalar equivalence model (Model 7) was established by making the all the item intercepts equal across groups, except the intercept of items EE3, FC2 and SI2. This model was nested with Model 3. Because the χ^2 of the full scalar invariance model was significantly greater ($\Delta\chi^2$ = 83.49, Δdf = 13, $p < 0.001$) than that of the partial metric model, full scalar invariance was rejected. Then, we applied the factor-ratio tests and the list-and-delete methodology to identify the non-invariant items. All intercepts except those belonging to PE3 and PE4 were found to be non-invariant across groups. Subsequently, a partial scalar invariance model was established by constraining the intercepts of items PE3 and PE4. The partial scalar invariance model fit the data well, and the χ^2 difference between this model and the full metric model was not significant ($\Delta\chi^2$ = 0.83, Δdf = 2, $p > 0.05$). Although we obtained partial metric and partial scalar invariance, the baseline measurement model cannot be compared across the groups because, except for the performance expectancy construct, none of the other constructs have at least two intercepts equal. This means that the origins of the scales are not the same across the users with no experience and at least some experience with focal technology, thereby making the comparison of latent means meaningless.

7.3. Summary of findings

Table 9 presents the summary of the findings of the invariance analysis on all respondent group characteristics. The configural invariance model showed model fit on all respondent group characteristics. This shows that the factor structure of the UTAUT baseline measurement model is the same across subgroups on all respondent group characteristics. The full metric invariance model held for all respondent group characteristics except for the user's general IT knowledge and experience with focal technology respondent group characteristics. Only partial metric invariance was established in these two respondent group characteristics. This means that users belonging to different groups in these respondent group characteristics perceive the scales of the UTAUT constructs differently. However, we recalibrated the scales by showing partial metric invariance. The factor loading of item EE1 was found to be non-invariant across groups in the user's general IT knowledge respondent group characteristic. In the respondent group characteristic user's experience with focal technology, the invariant sets of items for the effort expectancy construct were EE1, EE2 and EE4. For the facilitating conditions construct, two invariant sets (FC1, FC2, FC4) and (FC1, FC3, FC4), were identified. Similarly, for the social influence construct, two invariant sets (SI1 and SI4) and (SI2 and SI4), were identified. The model fit of the metric invariance model in all other respondent group characteristics shows that the users in these respondent group characteristics perceive the measures related to a set of underlying constructs to the same extent across groups. The full scalar invariance model held for all respondent group characteristics except for the user's familiarity with focal technology and

Table 9
Summary of invariance analysis on all respondent group characteristics.

Hypothesis	Respondent group characteristic	Configural	Metric	Uniqueness	Variance	Covariance	Scalar	Latent means comparison
H1	General IT knowledge	Yes	Partial EE1 is non-invariant	No	Yes	Yes	Yes	NS except EE, where $\alpha_{EE\_low} < \alpha_{EE\_high}$
H2	Specific IT knowledge-familiarity	Yes	Yes	No	Yes	Yes	Partial Non-invariant set: all items except PE3 and PE4	NA
H3	Specific IT knowledge – experience	Yes	Partial Non-invariant set: EE3, FC2 and SI2	Yes	Yes	No	Partial Non-invariant set: all items except PE3 and PE4	NA
H4	Usage pattern – total hours spent on a blog in the last month	Yes	Yes	Yes	Yes	Yes	Yes	NS except EE and IU, where $\alpha_{EE\_low} < \alpha_{EE\_high}$ $\alpha_{IU\_low} < \alpha_{IU\_high}$
H5	Usage pattern – numbers of hours spent on blog each time	Yes	Yes	Yes	Yes	Yes	Yes	NS except EE, SI and IU, where $\alpha_{EE\_low} < \alpha_{EE\_high}$ $\alpha_{SI\_low} < \alpha_{SI\_high}$ $\alpha_{IU\_low} < \alpha_{IU\_high}$
H6	Gender	Yes	Yes	No	No	Yes	Yes	NS

Yes – Invariance hypothesis accepted, No – Invariance hypothesis rejected, Partial – partial invariance accepted, NS – no significant difference between latent means of the constructs, α_i – latent mean of i, NA – latent means comparison is meaningless.

experience with focal technology respondent group characteristics. Only partial scalar invariance was established in these two respondent group characteristics, with just two of the intercepts proving to be invariant in both respondent group characteristics. This shows a clear shifting of origin of the scales among respondents belonging to the subgroups of these two respondent group characteristics. Due to the rejection of full scalar invariance and the presence of only two invariant intercepts, the scales of the UTAUT model are rendered incomparable across the subgroups of these two respondent group characteristics. However, the model fit of the scalar invariance model on all other respondent group characteristic measures shows that the latent means can be compared among respondents belonging to the subgroups of these respondent group characteristics. Uniqueness invariance was rejected for the user's gender, user's general IT knowledge and user's familiarity respondent group characteristics. This shows that the measurement model does not consistently measure the constructs with the same degree of error across most subgroups in a respondent group characteristic. The invariance of variances of constructs was rejected only in the user's gender respondent group characteristic, thereby making the comparison of covariances meaningless for that respondent group characteristic. However, the model fit of the invariance of variances of constructs on all other respondent group characteristics shows that valid comparisons of covariances can be made in those respondent group characteristics. Similarly, the invariance in covariance was rejected in only the user's experience with focal technology respondent group characteristic, showing that the measurement model does not adequately differentiate between the constructs among respondents belonging to the subgroups of this respondent group characteristic.

Because both classifications of users' specific IT knowledge showed that the latent means cannot be compared across subgroups, researchers should be cautious when using the UTAUT instrument in a sample with varying degrees of specific knowledge about the focal technology. Because both operationalizations of the user's usage pattern respondent group characteristic showed invariance on all tests of invariance, we can infer that researchers can use the UTAUT instrument in a sample with varying degrees of usage patterns. The same is the case with the user's gender respondent group characteristic, although uniqueness invariance and invariance in construct variance is not satisfied.

Finally, a comparison of latent means was performed. The effort expectancy construct had significantly different means in the user's general IT knowledge and in both operationalizations of the user's usage pattern respondent group characteristic. The intention to use construct had significantly different means in both operationalizations of the user's usage pattern respondent group characteristic. The social influence construct had significantly different means in the total hours spent on a blog each time measure of the user's usage pattern respondent group characteristic.

8. Limitations, future research directions, and contributions

8.1. Limitations

Before we discuss the contributions of this study, it is important to highlight its limitations. First, the sample in the present study consists of undergraduate students. This can certainly be viewed as a limitation because the findings of this study may not be as readily applicable to older working professionals as younger populations. However, our focus in this study was on new Web-oriented innovations, and blogs are one such innovation. Young people are adopting most of the newer web technologies, particularly web 2.0 technologies such as blogs, and students are an integral part of that population. Therefore, we believe our sample represents a large population that currently adopts new web-based technologies, and the findings of this study, therefore, may be broadly applicable.

Second, the sample in this study comes from Hong Kong. Asian countries are known to be culturally different than the US, and we cited a number of studies earlier in this article in the technology acceptance domain that have tested culture, nationality, or country as a grouping variable and that have found one or more TAM/UTAUT scales to fail one or more invariance tests. Therefore, the results of this study may not be as readily applicable in the US as in other Asian cultures, and the results of this study should, therefore, be interpreted with this limitation in mind.

Third, the group sample sizes for one of the two groups in two of the five technology engagement grouping variables – general computing knowledge (operationalization for general IT knowledge) and familiarity with blogs (operationalization for specific IT knowledge) – are relatively small. Although there is limited research on the sample size requirement for measurement invariance analysis, a simulation study shows that goodness-of-fit indices such as the CFI (reported in this paper) are independent of both the sample size and model complexity [17]. Our CFI values for the invariance hypotheses for these grouping variables were all above the accepted threshold of 0.90. Therefore, we believe this limitation does not affect the generalizability of our findings in a significant way. Nonetheless, we recommend that future invariance studies of the UTAUT instrument strive to achieve higher sample sizes for each group on each within-study grouping variable.

Finally, the group sizes on the six grouping variables in this study are not equal across the various groups. For example, there are 87 males and 163 females on the gender grouping variable. Similarly, the two group sizes on the other five grouping variables are also different. A Monte Carlo analysis-based study [16] shows that the differences in model fit between two groups on a grouping variable become larger when group sizes in an invariance study are equal rather than unequal. Therefore, differences in model fit between two groups on a grouping variable may be underestimated when group sizes on that variable are not equal. Consequently, some true non-invariance may remain undetected. This finding suggests that robust findings about the invariance of scales would be achieved with equal group sizes, and therefore, unequal group sizes may be deemed as a limitation of this study. However, it should be noted that our findings about the non-invariance of the UTAUT scales with respect to the "specific IT knowledge" variables are not affected by this limitation, as the model fit differences between the two groups on these variables are underestimates, not overestimates, of the true differences between these groups. Furthermore, our study is also in line with other invariance studies in the technology acceptance domain, cited in this paper, that also assess the invariance of TAM/UTAUT scales with unequal respondent group sizes, as equal group sizes are difficult to accomplish in practice.

8.2. Future research directions

The findings as well as the limitations of this study open up further avenues for research, as discussed above, but most clearly in three areas. First, our study uses a student sample to study invariance, thereby limiting the variety in age in our sample. Age is a very important within-study variable because younger people might understand the scales differently than middle-aged or older people. Hence, future invariance studies should consider respondents belonging to various age groups, such as young, middle-aged and older populations, to study the within-study invariance of the UTAUT. Second, more invariance studies of the UTAUT scales with users from countries and cultures other than Hong Kong should be conducted to develop a deeper understanding of the invariance of the UTAUT instrument. Third, more invariance studies should be conducted such that the number of observations in each respondent group is approximately the same so that more robust results are obtained. Fourth, the findings of this study provide some preliminary indication that there may be a need to redesign some scales for the UTAUT by taking into consideration how users with different levels of experience and familiarity with the focal technology perceive the UTAUT items. With a large sample, we find that two items, PE1 and PE2, do not load properly on the constructs. This is an indication that, despite the numerous studies on the UTAUT, the scales need to be refined in future studies, especially for younger populations. Finally, while we analyze UTAUT invariance using the very important within-study respondent group characteristics, i.e., those that pertain to a user's engagement with technology, there are other within-study variables that can impact the invariance of the UTAUT instrument, and they need to be studied in future research. For example, in a given sample, there can be respondents with varying levels of peer support. Not all respondents will have peers who have expertise in a technology under study. If a respondent has peers who are tech-savvy, the respondent's day-to-day interactions with those peers and the support the respondent would receive when using the technology might shape his evaluation of a focal technology. Consequently, respondents who have high peer support might understand the UTAUT instrument differently from those respondents who have low-peer support. Thus, future research must analyze the UTAUT's invariance properties with within-study variables, such as a respondent's peer support.

8.3. Contributions and implications

In this section, we present the key contributions of our paper and the implications of those contributions. Our study makes two significant contributions to the technology acceptance literature. First, to our knowledge, this is the first study that assesses the *within-study invariance* of the five key UTAUT scales by conducting a rigorous and comprehensive invariance analysis with a comprehensive set of six grouping variables, five of which capture the key aspects of respondents' engagement with technology in a deep and robust manner. Although previous studies have analyzed the invariance of a few within-study variables, this study is the first to make a clear distinction between within-study and across-study measurement invariance. This distinction is quite important, as all technology acceptance studies involve respondents who vary based on within-study variables, such as prior technology knowledge, which can potentially affect the invariance of the UTAUT instrument. Thus, we recommend that all researchers establish the within-study invariance of the UTAUT scale along the same lines as they establish, for example, instrument reliability and convergent and discriminant validity, before modeling the user acceptance of the focal technology in the study.

Furthermore, we theorize respondents' engagement with technology as a very important set of within-study grouping variables, and we test the invariance of the UTAUT instrument with five technology engagement variables. Given the technology context and the nature of the UTAUT instrument, variables pertaining to a respondent's engagement with technology are bound to vary in every UTAUT study. Our results show that the UTAUT scales were not invariant for and, thus, not similarly interpretable by respondent groups with varying levels of specific IT knowledge. We suggest that future studies be conducted to refine the scales so that users who have varying levels of knowledge of the focal technology understand the UTAUT instrument similarly. The UTAUT scale however, was fully invariant for respondent groups with varying usage patterns (for both operationalizations) and was partially invariant (with only one item being metric invariant) for respondent groups with varying levels of general IT knowledge. Based on these findings, we are confident that the UTAUT scales can be used in future technology acceptance studies to obtain credible results in samples where there are users with varying technology usage patterns and varying degrees of general IT knowledge.

In this context, it is also important to note that ours is also the first study to use a state-of-the art invariance testing methodology in establishing the within-study variables in the UTAUT context. Previous studies that have analyzed within-study variables have done so only in technology acceptance models other than the UTAUT model, with limited invariance tests and for a limited set of technology engagement variables. The one UTAUT study [39] that makes use of the full suite of invariance tests did not analyze any technology engagement-related within-study grouping variables (with gender as the only within-study variable tested). Thus, the present study fills this crucial gap in the literature on UTAUT invariance. Second, while making the above-mentioned contribution, this study also makes a subsidiary contribution by highlighting the respondent characteristics for which the UTAUT scales are invariant and those for which one or more of the UTAUT scales are non-invariant. The study also indicates items for all UTAUT scales that are found to be invariant and that can be safely used in future technology acceptance studies to generate valid and comparable results across different respondent groups. We found that the UTAUT scales are invariant across respondents' gender, their general IT knowledge, and their technology usage patterns with respect to the focal technology. However, we also found that some of the UTAUT scales are non-invariant with respect to respondents' specific IT knowledge. In cases where full invariance of the UTAUT scales was rejected, we drew upon the latest methods to establish partial invariance, and we identified partially invariant item sets for specific respondent group characteristics. Until further research is conducted, researchers may be advised to use the reduced set of UTAUT scale items when conducting technology acceptance studies to generate valid, reliable, and interpretable results.

Appendix A

A.1. Demographic data and respondents' blog usage patterns

Survey on opinion of weblogs

This questionnaire aims to collect participants' opinion of using **Weblog*. *Weblog* is becoming very popular. It affects all walks of life of Internet users. This study serves as a means to measure the determinants in the usage of *Weblog* and serves as a basis to provide recommendations for continuous improvement to *Weblog* implementation and development. All data collected will be used for statistical and research purposes only and will be kept strictly confidential.

Your participation in this survey is PURELY voluntary. However, your kind contribution is greatly appreciated. Thank you very much.

*Weblog, web log, or simply a blog is a web-based application, which contains periodic time-stamped posts on a common webpage. A number of sites provide weblog service and form a community that contains online diaries and journals of their users. You can easily start your own free journal, share thoughts with your friends and meet new friends using a weblog. A blogger refers to a person who maintains a blog under any blogging services.

PART A: Please answer or tick as appropriate.

1. What do you think your computer knowledge is:
☐ Very little ☐ Fair ☐ Good ☐ Expert

2. Are you familiar with *Weblog*?
☐ Not at all ☐ A little ☐ Familiar ☐ Very Familiar

3. How long have you been using weblog as stated above?
☐ Never ☐ Less than 1 year ☐ 1-2 years ☐ 3-4 years
☐ More than 4 years

4. In total, how long in the last month did you login your *Weblog*?
_____ hours _____ minutes

5. On average, every time, how much time do you spend on when you login your *Weblog*?
_____hours _____ minutes

6. Your gender: ☐ Male ☐ Female

Appendix B

B.1. Items used in estimating UTAUT in our paper

Performance expectancy	
PE1	If I use the system, I will increase my chances of achieving better performance.
PE2	I would find the system useful.
PE3	Using the system increases my productivity.
PE4	Using the system enables me to accomplish tasks more quickly.
Effort expectancy	
EE1	It would be easy for me to become skillful at using the system.
EE2	I would find the system easy to use.
EE3	My interaction with the system would be clear and understandable.
EE4	Learning to operate the system is easy for me.
Social influence	
SI1	People who are important to me think I should use the system.
SI2	People who are important to me have been helpful in the use of the system.
SI3	In general, my organization has supported the use of the system.
SI4	People who influence my behavior think I should use the system.
Facilitating conditions	
FC1	The system is compatible with other systems I use.
FC2	I have the knowledge necessary to use the system.
FC3	I have the resources necessary to use the system.
FC4	A specific person or group is available for assistance with system difficulties.
Behavior intention to use the system	
IU1	I predict I will use the system in the coming future.
IU2	I intend to use the system in the coming future.
IU3	I plan to use the system in the coming future.

Appendix C

C.1. Invariance analysis results

C.1.1. Familiarity with the focal technology

The results in Table A1 show that configural invariance was supported for the baseline measurement model (Model 1). Next, the full metric invariance model (Model 2) was established. This model was nested with Model 1. The fit of this model was acceptable and the model did not differ significantly from the Model 1. Next, the uniqueness invariance model (Model 3) was established. This model was nested with Model 2. Because, the χ^2 of the uniqueness invariance model was significantly greater ($\Delta\chi^2 = 51.43$, $\Delta df = 19$, $p < 0.001$) than that of the full metric invariance model, uniqueness invariance was rejected. Next, the invariance in the construct variance model (Model 4) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 2. Next, the invariance in construct covariance model (Model 5) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 2. Finally, the full scalar equivalence model (Model 6) was established. This model was nested with Model 2. Because, the χ^2 of the full scalar invariance model was significantly greater ($\Delta\chi^2 = 66.03$, $\Delta df = 16$, $p < 0.001$) than that of the full metric model, scalar invariance was rejected. Then, we applied the factor-ratio tests [20] and the list-and-delete methodology [19] to identify the non-invariant items. All intercepts except those belonging to PE3 and PE4 were found to be non-invariant across groups. A partial scalar invariance model (Model 7) was established by constraining the intercepts of items PE3 and PE4. This model was nested with Model 2. The partial scalar invariance model fit the data well, and the χ^2 difference between this model and the full metric model was not significant ($\Delta\chi^2 = 3.72$, $\Delta df = 2$, $p > 0.05$). Although we obtained full metric and partial scalar invariance, the baseline measurement model cannot be compared across the groups because, except for the performance expectancy construct, none of the other constructs have at least two intercepts equal. This means the origin of the scales is not the same across the users with low and high familiarity with the focal technology, thereby making the comparison of latent means meaningless.

C.1.2. User's gender

The results in Table A2 show that configural invariance was supported for the baseline measurement model (Model 1). Next, the full metric invariance model (Model 2) was established. This model was nested with Model 1. The fit of this model was acceptable and the model did not differ significantly from Model 1. Next, the uniqueness invariance model (Model 3) was established. This model was nested with Model 2. Because, the χ^2 of the uniqueness invariance model

Table A1
Invariance analysis by specific IT knowledge – familiarity with focal technology.

Model	Test of equivalence	Unconstrained vs. constrained models	*df*	χ^2	χ^2/df	RMSEA	IFI	TLI	CFI	Δdf	$\Delta\chi^2$	*p*-value
1	Configural invariance		182	304.66	1.67	0.05	0.91	0.88	0.91			
2	Full metric invariance	1 vs. 2	193	323.70	1.68	0.05	0.91	0.88	0.91	11	19.05	0.06
3	Uniqueness invariance	2 vs. 3	212	375.13	1.77	0.06	0.88	0.87	0.88	19	51.43***	0.00
4	Construct variance invariance	2 vs. 4	198	327.40	1.65	0.05	0.91	0.89	0.91	5	3.70	0.59
5	Construct covariance invariance	2 vs. 5	203	332.57	1.64	0.05	0.91	0.89	0.91	10	8.86	0.55
6	Full scalar invariance	2 vs. 6	209	389.74	1.87	0.06	0.87	0.85	0.87	16	66.03***	0.00
7	Partial Scalar invariance	2 vs. 7	195	327.42	1.68	0.05	0.91	0.88	0.90	2	3.72	0.16

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2
Invariance analysis by user's gender.

Model	Test of equivalence	Unconstrained vs. constrained models	*df*	χ^2	χ^2/df	RMSEA	IFI	TLI	CFI	Δdf	$\Delta\chi^2$	*p*-value
1	Configural invariance		182	293.21	1.61	0.05	0.93	0.91	0.93			
2	Full metric invariance	1 vs. 2	193	312.51	1.62	0.05	0.93	0.91	0.93	11	19.30	0.06
3	Uniqueness invariance	2 vs. 3	212	397.47	1.88	0.06	0.87	0.87	0.88	19	84.96***	0.00
4	Invariance in construct variance	2 vs. 4	198	326.15	1.65	0.05	0.92	0.90	0.92	5	13.67*	0.02
5	Invariance in construct covariance	2 vs. 5	203	318.49	1.57	0.05	0.93	0.91	0.93	10	5.982	0.82
6	Full scalar invariance	2 vs. 6	209	329.08	1.58	0.05	0.93	0.91	0.93	16	16.56	0.41

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3
Differences between latent means of males and females.

Construct	Difference in latent means	Standard error	Critical ratio	*p*-value
Performance expectancy	0.04	0.13	0.32	0.75
Effort expectancy	0.14	0.11	1.32	0.19
Social influence	0.14	0.12	1.17	0.24
Facilitating conditions	0.08	0.08	0.97	0.33
Intention to use	−0.11	0.13	−0.86	0.39

Goodness-of-fit statistics for the latent means comparison model.
$\chi^2 = 322.41$, $df = 204$, $p < 0.001$, $\chi^2/df = 1.58$, RMSEA = 0.05, IFI = 0.93, TLI = 0.91, CFI = 0.93.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

was significantly greater ($\Delta\chi^2 = 84.96$, $\Delta df = 19$, $p < 0.001$) than that of the full metric invariance model, uniqueness invariance was rejected. Next, the invariance in the construct variance model (Model 4) was established. This model was nested with Model 2. Because, the χ^2 of the invariance in construct variance model was significantly greater ($\Delta\chi^2 = 13.67$, $\Delta df = 5$, $p < 0.05$) than that of the full metric invariance model, invariance in construct variance was rejected. Next, the invariance in the construct covariance model (Model 5) was established. This model was nested with Model 2. The fit of this model was acceptable and the model did not differ significantly from Model 2. Finally, the full scalar invariance model (Model 6) was established. This model was nested with Model 2. The fit of this model was acceptable and the model did not differ significantly from Model 2. Because we obtained full metric and full scalar invariance, the baseline measurement model is invariant across males and females. Hence, the latent means can be compared across the groups.

To compare the latent means, in Model 6, the latent means of females was set to zero and that of males was set free to vary. This new model was estimated. The estimated factor mean of the male group is the difference between the latent means of males and females on the five main constructs of the UTAUT model. Table A3, shows the estimated difference in latent means and the model fit of this new model. Our results show that the model fit was acceptable. There was no significant difference between the latent means of the five main constructs of the UTAUT model across the two groups.

C.2. Technology usage pattern

C.2.1. Total hours spent on a blog in the last month

The results in Table A4 show that configural invariance was supported for the baseline measurement model (Model 1). Next, the full metric invariance model (Model 2) was established. This model was nested with Model 1. The fit of this model was acceptable, and the model did not differ significantly from Model 1. Next, the uniqueness invariance model (Model 3) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 3. Next, the invariance in construct variance model (Model 4) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 2. Next, the invariance in construct covariance model (Model 5) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 2. Finally, the full scalar invariance model (Model 6) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 2. Because we obtained full metric and full scalar invariance, the baseline measurement model is invariant across males and females. Hence, the latent means can be compared across the high and low usage groups measured by total hours spent on a blog in the last month.

Table A4
Invariance analysis by usage pattern – total hours spent on a blog last month.

Model	Test of equivalence	Unconstrained vs. constrained models	*df*	χ^2	χ^2/df	RMSEA	IFI	TLI	CFI	Δdf	$\Delta\chi^2$	*p*-value
1	Configural invariance		182	301.17	1.66	0.05	0.93	0.90	0.92			
2	Full metric invariance	1 vs. 2	193	314.43	1.63	0.05	0.92	0.90	0.92	11	13.26	0.28
3	Uniqueness invariance	2 vs. 3	212	334.27	1.58	0.05	0.92	0.91	0.92	19	19.84	0.40
4	Invariance in construct variance	2 vs. 4	198	318.03	1.61	0.05	0.92	0.90	0.92	5	3.59	0.61
5	Invariance in construct covariance	2 vs. 5	203	323.99	1.560	0.05	0.92	0.91	0.92	10	9.56	0.48
6	Full scalar invariance	2 vs. 6	209	327.87	1.57	0.05	0.92	0.91	0.92	16	13.43	0.64

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To compare the latent means, in Model 6, the latent means of the high usage group was set to zero and that of low usage was set free to vary. This new model was estimated. The estimated factor mean of the low usage group is the difference between the latent means of the two groups on the five main UTAUT model constructs. Table A5, shows the estimated difference in latent means and the model fit of this new model. Our results show that the model fit was acceptable. The latent mean of the effort expectancy and intention to use constructs was lower in the low usage group. There was no significant difference between the latent means of the other three UTAUT constructs across the two groups.

C.2.2. Number of hours spent on a blog each time

The results in Table A6 show that configural invariance was supported for the baseline measurement model (Model 1). Next, the full metric invariance model (Model 2) was established. This model was nested with Model 1. The fit of this model was acceptable, and the model did not differ significantly from Model 1. Next, the uniqueness invariance model (Model 3) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 3. Next, the invariance in construct variance model (Model 4) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 2. Next, the invariance in construct covariance model (Model 5) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 2. Finally, the full scalar invariance model (Model 6) was established. This model was nested with Model 2. The fit of this model was acceptable, and the model did not differ significantly from Model 2. Because we obtained full metric and full scalar invariance, the baseline measurement model is invariant across the high and low usage groups measured by total hours spent in the last month. Hence, the latent means can be compared across the high and low usage groups measured by the number of hours spent on a blog each time.

To compare the latent means, in Model 6, the latent means of the high usage group was set to zero and that of the low usage group was set free to vary. This new model was estimated. The estimated factor mean of the low usage group is the difference between the latent means of the two groups on the five main variables of the UTAUT model. Table A7, shows the estimated difference in latent means and the model fit of this new model. Our results show that the model fit was acceptable. The latent means of the effort expectancy, social influence and intention to use constructs were lower in the low usage group. There were no significant differences between the latent means of the other two UTAUT constructs across the two groups.

Table A5
Differences between latent means of high and low usage groups using the total of hours spent on a blog last month measure.

Construct	Difference in latent means	Standard error	Critical ratio	p-value
Performance expectancy	−.05	.13	−.37	0.72
Effort expectancy	−.22*	.10	−2.08	0.04
Social influence	−.24	.12	−1.93	0.05
Facilitating conditions	−.11	.07	−1.46	0.14
Intention to use	−.30*	.12	−2.45	0.01

Goodness-of-fit statistics for the latent means comparison model.
$\chi^2 = 319.77$, $df = 204$, $p < 0.001$, $\chi^2/df = 1.58$, RMSEA = 0.05, IFI = 0.93, TLI = 0.91, CFI = 0.92.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A6
Invariance analysis by usage pattern – numbers of hours spent on blog each time.

Model	Test of equivalence	Unconstrained vs. constrained models	df	χ^2	χ^2/df	RMSEA	IFI	TLI	CFI	Δdf	$\Delta\chi^2$	p-value
1	Configural invariance		182	314.64	1.73	0.05	0.92	0.89	0.92			
2	Full metric invariance	1 vs. 2	193	325.77	1.69	0.05	0.92	0.90	0.92	11	11.13	0.43
3	Uniqueness invariance	2 vs. 3	212	348.94	1.65	0.05	0.91	0.90	0.91	19	23.18	0.23
4	Invariance in construct variance	2 vs. 4	198	329.36	1.66	0.05	0.92	0.90	0.92	5	3.60	0.61
5	Invariance in construct covariance	2 vs. 5	203	340.90	1.68	0.05	0.91	0.90	0.91	10	15.14	0.13
6	Full scalar invariance	2 vs. 6	209	339.70	1.63	0.05	0.92	0.90	0.92	16	13.93	0.60

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A7
Differences between latent means of high and low usage groups using the number of hours spent on a blog each time measure.

Construct	Difference in latent means	Standard error	Critical ratio	p-value
Performance expectancy	.025	.137	.182	0.86
Effort expectancy	−.321**	.109	−2.947	0.00
Social influence	−.260*	.132	−1.967	0.04
Facilitating conditions	−.143	.079	−1.816	0.07
Intention to use	−.432***	.126	−3.413	0.00

Goodness-of-fit statistics for the latent means comparison model.
$\chi^2 = 357.45$, $df = 204$, $p < 0.001$, $\chi^2/df = 1.75$, RMSEA = 0.06, IFI = 0.90, TLI = 0.88, CFI = 0.90.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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