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A Cross-Continent Analysis of the Invariance of Product Information in Cross-Border Electronic Commerce

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ABSTRACT

Cross-border electronic-commerce (CBEC) is growing. However, due to differences in culture, habits, history, and language, among other factors, consumers in different regions may have different perception towards the same product information on CBEC platforms, which may lead to differences in their cognition of the product with implications for purchase intentions. Presently, little research has attempted to understand whether there are such differences between global consumers through the examination of measurement invariance (MI) in CBEC environments. By using multiple-group confirmatory factor analysis (MG-CFA), this study explored the invariance of two product information cognitions on CBEC platforms, namely product description and product awareness, among consumers in North America, Europe, Latin America, and Oceania. Data was collected from users of a popular CBEC platform in China. The authors find no significant differences in understandings and levels of awareness of product information across the four groups of consumers.

KEYWORDS

Cross-Border Electronic-Commerce, Cross-Continent Analysis, Measurement Invariance, Multiple-Group Confirmatory Factor Analysis, Product Awareness, Product Description

INTRODUCTION

Cross-border electronic-commerce (CBEC) provides new means and opportunities for enterprises to compete in international markets (Giuffrida, Mangiaracina, Perego, & Tumino, 2017). As a new form of e-commerce (Mou, Cohen, Dou, & Zhang, 2019), CBEC is weakening trade barriers among countries around the world (Zhu, Mou, & Benyoucef, 2019) and is having an unprecedented impact on global transactions. In 2018, global B2C CBEC transactions exceeded US$ 650 billion and were predicted pre-covid pandemic to reach US$ 994 billion in 2020 (Ebrun, 2018). The penetration rate of global cross-border online shopping has reached 51.2%, and the proportion of consumers who use CBEC accounts for 70% in regions such as the Middle East (iiMedia Research, 2019). Currently, America is the largest and most popular CBEC target market in the world (Chinabrands, 2018). Western Europe is another large e-commerce market with the highest CBEC penetration rates found in the Macedonian region and in Portugal (iiMedia Research, 2019). In addition, CBEC accounts for 25% of the Australian e-commerce market, with Australian online shoppers often preferring cross-border

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purchases of products from America and the UK. In Latin America, the development of CBEC in Brazil is relatively mature, and CBEC in Argentina is rapidly developing (iiMedia Research, 2019). In China, the scale of CBEC transactions reached 9.1 trillion yuan, and the scale of users exceeded 100 million in 2018 (iiMedia Research, 2019). According to data from Cifnews (2018), 57% of global online shoppers purchased goods from overseas retailers in the past six months. By continent, the average online consumer cross-border shopping rate is 63.4% in Europe, 45.5% in North America, 54.6% in Latin America, 55.5% in Africa and 57.9% in Asia-Pacific.

CBEC brings a variety of benefits to all parties around the world. However, due to differences in culture, habits, history and language (Yin & Choi, 2021), global consumers may have different cognitions of the same product information presented to them on CBEC platforms. Even for consumers in the same country, their attitudes, behaviors, and socioeconomic and geographic conditions are not completely the same (Ma, Lin, & Pan, 2021), which may lead to different views of the same product. Product information cognition is an issue that cannot be ignored in CBEC. The organization of information affects not only how much information consumers retrieve but also what information consumers retrieve (Cowley & Mitchell, 2003). If consumers misunderstand product information, then they could make incorrect judgements about a product, or buy a product that they do not expect (Zhu et al., 2019). More importantly, in CBEC, buyers and sellers are often from different countries, and they are not necessarily familiar with each other, so product information, which serves as a bridge between buyers and sellers, will have a critical impact on the transaction (Mou, Zhu, & Benyoucef, 2019). Past research shows that perceptions of product information are related inter-alia to online consumer trust (Kim, Ferrin, & Rao, 2008) and utilitarian benefits (Chiu, Wang, Fang, & Huang, 2014), while product uncertainty is a pre-contractual uncertainty that reduces purchase intentions (Mou et al., 2019) and willingness to pay price premiums (Dimoka, Hong, & Pavlou, 2012). Because distance factors in CBEC heighten uncertainty and complicate the correction of purchase errors (Kim, Dekker, & Heij, 2017), CBEC consumers may place a greater reliance on product information than consumers in domestic e-commerce. In this sense, compared with domestic e-commerce, consumers' cognitions of product information may be more salient to CBEC purchase decisions. Yet, CBEC platforms show little appreciation for these potential differences in product information cognition, and tend to assume invariance across international consumer populations when deciding on product information content and display (Kim, 2019). To advance CBEC research and practice, it is necessary to test the validity of these assumptions and determine whether international consumer cognitions of product information are invariant. Based on the above considerations, we propose the following research question:

RQ: Are consumers' cognitions of product information invariant in CBEC?

In response to this question, this study analyzes invariance in cognitions of product information among CBEC consumers around the world, with the purpose of evaluating the degree of similarity and difference in product information cognition of global consumers. Currently, studies on CBEC have mainly focused on delivery (Kim et al., 2017), dispute resolution (Ong & Teh, 2016), laws and regulations (Chen & Yang, 2017), and purchase intentions (Mou et al., 2019). Little research has addressed the measurement invariance (MI) of product information in CBEC settings. Therefore, exploring the MI of product information in CBEC is expected to obtain innovative research conclusions. In addition, to test this invariance more comprehensively, we innovatively focus on two important dimensions of product information: product description and product awareness, and use a multiple-group confirmatory factor analysis (MG-CFA) to evaluate the invariance of views of product descriptions and levels of product awareness among users of a Chinese CBEC platform based in four global regions (North America, Europe, Latin America and Oceania).

The main contribution of this research is to test the invariance of product information in a CBEC setting. Specifically, we measure the invariance of perceptions of product descriptions and levels of

product awareness among consumers across four regions. In other words, our MI test involves the study of global consumers' cognitions. Currently, most existing MI research focuses on measuring non-cognitive emotions such as depression, or constructs such as personality and intelligence quotient (IQ) (Fang, Wen, & Prybutok, 2014). However, MI of cognitive factors is growing (Mak, Young, Watanabe, Ramos, & Nam, 2020), and is particularly appropriate and necessary in the study of CBEC platforms. Given that CBEC platforms have become one of the main shopping channels for global consumers and that many products are unfamiliar to international consumers, it remains an open question as to whether consumers in different regions have different cognitions of the same product information. The study's results will help clarify for sellers whether there are differences in consumers' cognitions of the same product information across four regions in CBEC shopping settings. According to our results, sellers can take different measures to optimize product information for consumers in different regions of the world and create better marketing outcomes. In addition, this research can be of use to academics and practitioners in analyzing the various impacts of product information delivered through CBEC and in conducting cross-cultural studies or comparative analyses in light of different understandings of information.

In the remainder of this paper, first, we reviewed and described the theoretical background on product information in e-commerce, discuss past research on MI, and then outline MI test procedures. Second, the research methodology is described in detail. Third, data analysis results of MI test are presented. Finally, we discuss the conclusions, implications and limitations.

THEORETICAL BACKGROUND

Role of Product Information in E-Commerce

Product information refers to information broadly related to the product (Krefeld-Schwalb & Rosner, 2020; Saaksvuori & Immonen, 2008), which can have an impact on consumers' perception, cognition, consciousness, emotion, behavior and other activities. Nowadays, product information has always been an important focus of research in the field of e-commerce. At present, many researchers have analyzed the effects of various kinds of product information on consumers and sellers using various types of e-commerce models. For instance, Hong and Wyer (1989) analyzed the impacts of product attribute information and country-of-origin on product evaluation and found a product's country of origin to affect product evaluations and encouraged consumers to pay more attention to attribute information. Lee and Lee (2009) evaluated the product information inference process in an electronic word-of-mouth (eWOM) context. Their results show that inferred product information was only displayed when a consumer exhibited decisive behavior. In addition, other scholars have developed different systems for analyzing and applying product information in e-commerce and have drawn meaningful conclusions as a result. Manvi and Venkataram (2005) proposed a distributed proxy-based e-shopping model that can intelligently evaluate consumers' behaviors and then display appropriate product information. Omelayenko and Fensel (2001) analyzed problems with the process of product information integration and proposed a three-layered product integration framework and two-layered integration approach to business-to-business (B2B) e-commerce. Currently, there have been few studies on product information in CBEC. For instance, Zhu et al. (2019) evaluated the impact of product information on purchase intention in CBEC. The empirical analysis results showed that platform emotion can mediate the positive significant influence of product information on consumers' purchase intention.

With the gradual development of product information research, product descriptions have received increasingly more attention as an important facet of product information. In a broad sense, product description is the expression and description of product information and includes two parts: product content and product display (Lin, Featherman, Brooks, & Hajli, 2019; Wang, Li, Ye, & Law, 2016). Among them, product content refers to the information content related to the product, while product display refers to the way in which the information content will be presented. Currently, there are several works on product descriptions in the field of e-commerce. Some scholars have evaluated

heterogeneity in product descriptions. For instance, Ng, Yan, and Lim (2000) proposed that there were two ways to solve the problem of information heterogeneity in e-commerce: standardization and integration, and briefly introduced the specific application process of these ways. Similarly, Fensel et al. (2001) analyzed heterogeneity in product descriptions used in B2B e-commerce settings and proposed a product description integration process involving structured product description, classified product description, multiclassified product description and personalized product description. Other researchers have also tried to build systems and models to improve product descriptions. For intelligent e-commerce, Schulten et al. (2001) proposed a general model and working solution that can generate feasible product descriptions based on two different product classification standards. In addition, it is worth noting that studies related to product description have also emerged in the field of CBEC. For example, Mou et al. (2019) investigated the impact of product description on purchase intention in CBEC, and found that product description can produce a positive significant effect on purchase intention through product involvement and platform involvement respectively.

Relative to this focus on product descriptions, there is less literature on product awareness. Product awareness refers to the ability of consumers to recall or recognise a product, or simply whether or not consumers know about a product (Zhu et al., 2019). So far, in the field of e-commerce, studies related to awareness mainly focus on consumer (Huang, Yang, & Zheng, 2019; Barroso & Llobet, 2012; Lee, Suh, & Whang, 2003), brand (Wang & Chen, 2019; Barreda, Bilgihan, Nusair, & Okumus, 2015; Lu, Chang, & Chang, 2014), and e-commerce (Papazafeiropoulou, Pouloudi, & Doukidis, 2002). As far as product awareness is concerned, Farshcian (2001) analyzed the importance of this factor and introduced a product awareness model and described its design and implementation. So far, there has been no research related to product awareness in the field of CBEC.

In addition, each market has its own cultural boundaries. In the e-commerce market, consumers have a unique sensitivity to culture. The culture differences can affect consumers' behavioral tendencies in e-commerce, because it can play a non-negligible role in consumers' perception of online services (Ahluwalia & Merhi, 2020). Presently, several studies have also analyzed this issue in recent years. For instance, Hallikainen and Laukkanen (2018) evaluated the impact of culture differences between China and Finland on consumers' behaviors in e-commerce, and finally found that this culture difference caused consumers in the two countries to produce different shopping trust disposition. Furthermore, Yu and Kim (2019) compared the online markets in China and the US, and revealed that online fashion retailers in China, the US and Western Europe were more inclined to provide loose return policies in the US market, which may reduce consumers' perception of uncertainty.

Despite the existence of literature on product information, product descriptions, product awareness and culture differences, few studies relate specifically to CBEC. Due to the globalization, multilingualism and multiculturalism of CBEC, sellers aim to provide product information that can be easily understood by global consumers on CBEC platforms. However, this kind of product information may not conform to the habits and preferences of consumers in every country. In other words, the product information may be different on traditional e-commerce platforms and foreign e-commerce platforms. On the traditional e-commerce platforms, appropriate and positive product information can stimulate consumers' memories and improve their cognition, then affecting their subsequent shopping behaviors (Mou, Cui, & Kurcz, 2020). However, this conclusion may not necessarily apply in CBEC. On CBEC platforms that are not familiar to global consumers (Cui, Mou, Cohen, Liu, & Kurcz, 2019), product information cognition is the primary issue. When consumers misunderstand product information, they are not able to make the right decisions or engage in the right behaviors (Cheong & Morrison, 2008) on these platforms. Considering the importance of this primary issue, it is necessary to analyze the cognitive invariance of product information in CBEC in this research. In addition, few studies on product awareness have been conducted from the perspective of behavior. Product awareness reflects the mental link between consumer attention and product information. When this link is established, the consumer will make a decision. In this sense, product awareness is a source of consumer shopping behavior that will have different degrees of influence on consumers'

interests, desires, motivations, needs and other characteristics (Mou et al., 2020). In view of that, in this study we innovatively regard product awareness as an important dimension of product information, and construct a measurement model of product information by associating product description with product awareness. In addition, considering that there is no invariant analysis of product information cognition in the existing researches of CBEC, we innovatively try to evaluate the invariance of product information cognition of consumers across four continents. Therefore, this study is of significant innovation and research value.

Measurement Invariance (MI) in E-Commerce

According to the research of Fang, Prybutok, and Wen (2016), MI refers to the invariance of latent variable measurement across groups. In other words, MI is achieved when the relationship between indicators and a latent construct is identical across groups (Drasgow & Kanfer, 1985). Research on measurement invariance has been carried out for more than forty years. MI research originated in the field of psychology and has since extended from psychology (Whisman et al., 2020; Bowden, Saklofske, Van de Vijver, Sudarshan, & Eysenck, 2016; Rutkowski & Svetina, 2014) to other research fields such as survey methodology (Fang et al., 2016; Cheung & Rensvold, 2002), education (Steinmetz, Schmidt, Tina-Booh, Wieczorek, & Schwartz, 2009; Schweig, 2014), marketing (He, Merz, & Alden, 2008; Henseler, Ringle, & Sarstedt, 2016), and so forth.

MI tests are gaining attention in the field of e-commerce. For instance, Walsh, Shiu, Hassan, Hille, and Takahashi (2019) tested the measurement invariance of the full and short scales for fear of online identity theft (FOIT) in e-commerce across the United States, Germany, and Japan. The test results revealed that while configural invariance existed for the short FOIT scale, the full FOIT scale yielded partial metric invariance across the three countries, indicating that consumers in the three countries had different cognitions of this issue. In a model of risk and convenience in the field of B2B e-services, Matos and Krielow (2019) tested for measurement invariance before pooling data from three industries. San Martín, Camarero, and San José (2011) analyzed the MI of cross-national e-commerce and found that their theoretical model exhibited factorial invariance between Spanish and Japanese e-commerce platforms. Lucia-Palacios, Bordonaba-Juste, Polo-Redondo, and Grünhagen (2014) examined the MI of all items in the scale used for Spanish and American e-commerce firms. A detailed analysis of results of each factor showed that the scalars were invariant while the intercepts were significantly non-invariant. This meant that the e-commerce samples in these two countries had some cognitive similarities and differences on the items in the scale. In addition, Herrando, Jiménez-Martínez and Hoyos (2019) tested the measurement invariance of composites models in the social commerce, and found that each construct in the model satisfied partial measurement invariance, indicating that the consumers had invariant cognition of the measurement items. Lai and Li (2005) examined the measurement invariance of technology acceptance model (TAM) across different gender, age, and information technology (IT) competence subgroups. The analysis results suggested that male and female, old and young, IT expert and novice, conceptualized the TAM construct in very similar ways. Hallikainen and Laukkanen (2020) tested whether the measurement items in the scale of trustworthiness were invariant in both China and Finland. The findings showed that the scale had metric invariance but not scalar invariance in the two countries, which implied that Chinese and Finnish e-commerce consumers had different understanding and awareness of trustworthiness in e-commerce.

The vast majority of the research on MI conducted in the field of e-commerce focuses on the traditional e-commerce environment while articles related to CBEC are extremely scarce. In CBEC settings, consumers come from different regions and countries and have different geographic backgrounds and consumption habits. For the same product, consumers from different regions usually have varied understandings of its description and awareness. In this sense, if sellers intend to carry out e-commerce targeted at consumers around the world, it is extremely important to explore consumers' own understandings of product information across regions. In view of the shortcomings of existing research, this study will explore the MI of product information given in CBEC settings across North

America, Europe, Latin America and Oceania, which will have important theoretical and practical implications for CBEC researchers and practitioners.

MI Test Procedures

So far, testing of MI has mainly involved the use of two research approaches: MG-CFA and item response theory (IRT). Many scholars have compared similarities and differences between the two methods (Raju, Laffitte, & Byrne, 2002; Gonzalez-Roma, Tomas, Ferreres, & Hernandez, 2005). Although the analysis results of the two methods are consistent, in terms of the linear model selected in this study, MG-CFA presents obvious advantages over IRT when processing multiple latent variables and multiple group samples. Moreover, with the development of structural equation modeling technology, we can now use suitable software for MG-CFA while applications of IRT remain relatively complex. For the above two reasons, we adopt MG-CFA to test MI. Therefore, in this paper, we only describe procedures of MG-CFA in detail.

We draw on previous research (Vandenberg & Lance, 2000) to examine the following seven invariance hypotheses for MI testing of CBEC product information understanding across four groups of consumers (North America, Europe, Latin America and Oceania).

Step 1: Hypothesis H_1 postulates that the variance-covariance matrices of all measurement items are invariant across groups ($\sum^{(1)}=\ldots=\sum^{(4)}$) where $\sum$ denotes the item variance-covariance matrices while (1) and (4) represent the studied groups. If the hypothesis is met, this means that there is indeed MI among the groups, and a subsequent test of MI is unnecessary. In other words, in this study, H_1 tests whether global consumers have the same understanding and degrees of awareness of product information on a CBEC platform. If this is not the case, we follow the subsequent test procedures to determine the level of MI among the four groups.

Step 2: Hypothesis H_2 postulates that the same pattern of fixed and free factor loadings is specified across groups ($form^{(1)}=\ldots=form^{(4)}$) where form denotes the number of factors and the structural model. This test is called the configural invariance test or weak factorial invariance test (Vandenberg & Lance, 2000). If this hypothesis can be supported, we can divide the data obtained from every group into the same number of factors with the same items associated with every factor (Fang et al., 2016). This test forms the premise and basis of the subsequent test. If this hypothesis is not supported, consumers of different regions have different understandings of product information in CBEC environments. In this sense, subsequent tests will be meaningless.

Step 3: Hypothesis H_3 postulates that in addition to configural invariance (H_2), factor loading matrices are invariant across groups ($\Lambda^{(1)}=\ldots=\Lambda^{(4)}$) where Λ denotes the factor loading matrices. This test is called the strong factorial invariance test (Vandenberg & Lance, 2000) and forms the basis of MI. If this hypothesis can be met, the means of the original scores on all measurement items can be interpreted meaningfully across all four groups. This means that for every unit of change in a given factor, the item varies equally across groups (Fang et al., 2014). In other words, in this study, the existence of factor loading matrix invariance denotes no significant difference in consumers' understandings and degrees of awareness of product information across different regions.

Step 4: Hypothesis H_4 postulates that in addition to factor loading matrix invariance (H_3), the correlation coefficients between factors are invariant across groups ($\varphi^{(1)}=\ldots=\varphi^{(4)}$) where φ is the factor correlation coefficient. When there are two or more factors in the model, we tend to pay more attention to the correlations between factors (Fang et al., 2016). Many studies have combined this test with the following test. To obtain more detailed results, we separately test the MI of factor correlation coefficients to analyze the invariance between product understandings and levels of product awareness across different regions.

Step 5: Hypothesis H_5 postulates that in addition to factor correlation coefficient invariance (H_4), the variances of all factors are invariant across groups ($\Phi^{(1)}=\ldots=\Phi^{(4)}$) where Φ denotes the factor variance-covariance matrices. This test is designed to analyze the MI of factor variances. The

differences in factor variances are regarded as revealing group differences in the calibration of true scores. After this test, we can judge whether deviations in consumers' product understandings and levels of product awareness are invariant across regions.

Step 6: Hypothesis H_6 postulates that in addition to factor variance invariance (H_5), the intercepts of all measurement items are invariant across groups ($\tau^{(1)}=\ldots=\tau^{(4)}$) where τ indicates the intercepts of all measurement items. This test is called the scalar test (Vandenberg & Lance, 2000). If the intercept is invariant, differences in item scores will completely reflect the differences between factors. Otherwise, there is no equivalent zero value for every measurement item, and the cross-group measurement has systematic deviations (Fang et al., 2016). In this test, we analyze whether the starting points of consumers' understandings and levels of awareness are the same for all measurement items.

Step 7: Hypothesis H_7 postulates that in addition to item intercept invariance (H_6), the variance-covariance matrices of all measurement errors are invariant across groups ($\Theta^{(1)}=\ldots=\Theta^{(4)}$) where Θ indicates the variance-covariance matrices of measurement errors. If this hypothesis can be met, the variation differences in item scores will completely reflect the variation differences in factors across groups (Vandenberg & Lance, 2000). In other words, the differences in consumers' scores on survey questions reflect their different opinions and views on these questions.

Among the above test procedures, step 1 involves the omnibus test. From steps 2 to 7, the former hypothesis test forms the basis of the latter hypothesis test. Only after the previous test is satisfied can we proceed to the next test. When a test is not met, the MI test will be terminated. The purpose of test procedures used in this study is to test the invariance of factor correlation coefficients for different regions, i.e., Step 4. The overall test procedures are shown in Figure 1.

METHODOLOGY

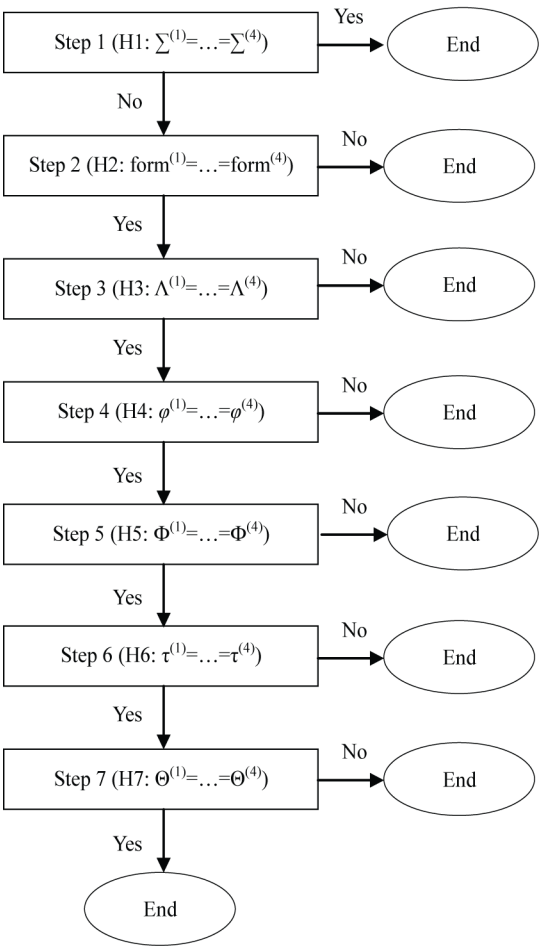
Measures

We used two variables, product description (PD) and product awareness (PA), to measure product information. The PD scale reflected the consumers' self-views on how easy it was for them to understand the product information given on the CBEC platform; while the PA scale denoted the consumers' levels of awareness and recollection of these products listed on the CBEC platform.

We designed six measurement items related to the two scales based on the research of Smith, Chen, and Yang (2008). In order to make it easier for consumers to express their views on all items, we used a 5-point Likert scale (1=completely disagreement, and 5=completely agreement) to measure each item. The PD scale includes three measurement items (PD1: The products descriptions are easy to understand on this platform.; PD2: I am able to comprehend the descriptions made in the products on this platform.; PD3: The products descriptions are hard to understand on this platform (Reverse).), and the PA scale is also composed of three measurement items (PA1: I am aware of the products on this platform.; PA2: I can recall the products on this platform.; PA3: I can recognize the products on this platform.). In consumer research, previous studies show that awareness can facilitate information understanding (Smith et al., 2008). Similarly, understanding can enhance consumers' recollection of information, which will influence consumers' levels of awareness (MacInnis & Jaworski, 1989). Therefore, there is a certain correlation between PD and PA. The conceptual model of factors and measurement items used in the present study is shown in Figure 2. In this model, PD and PA are both exogenous variables. In addition, we adopted the fixed loading method to establish the conceptual model, and used the MG-CFA to test the MI of product information across four continents.

We use these two scales for the following reasons. First, product description understanding and product awareness are two important factors related to product information (Zhu et al., 2019). The two scales capture consumers' understanding and recall of product information. Therefore, using

Figure 1. Overall MI test procedures in this research

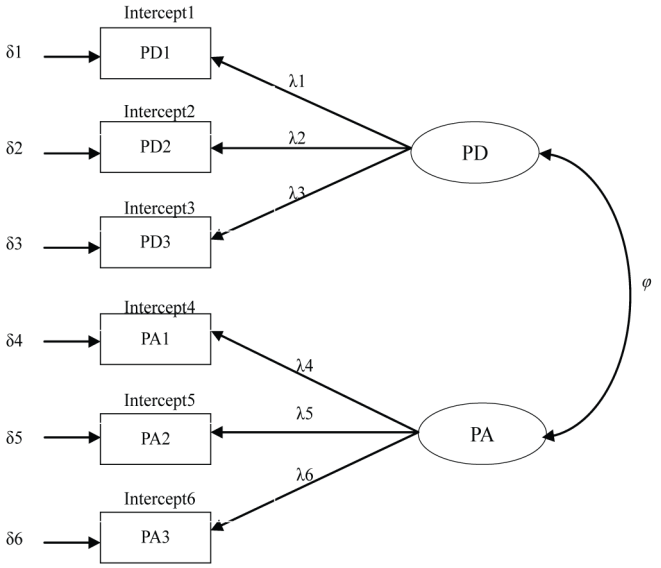


the two scales for testing can essentially find the invariance and difference in cognitions of product information among consumers in CBEC environments. Second, the two scales are related to some extent (Zhu et al., 2019), and we can test the invariance in factor correlation coefficients. Currently, there are not many studies that specifically tested the invariance of factor correlation coefficients. As a result, detailed invariance results between product understanding and product awareness can be obtained. Third, as the measurement content of the two scales concerns the actual shopping experiences of consumers, we can realize the consumers' sensitivities to product information on a CBEC platform and can easily obtain valuable analysis results about the MI among different regions. Finally, the scale items are relatively straightforward and should be easy enough for consumers to complete. The simple structures enable consumers to easily understand the scales, thus helping to avoid the potential misunderstandings. In addition, short scales are less likely to induce boredom or fatigue in consumers.

Data Collection

We collaborated with DHGate.com, a well-known Chinese CBEC platform, in executing data collection. Established in 2004, DHGate.com was the first online platform for SMEs to complete B2B cross-border transactions in China.

Figure 2. Conceptual model of factors and measurement items



We collaborated with DHGate.com for a number of reasons. DHGate.com is a global online website that operates as a CBEC platform. The platform has carried out global online trade for more than 15 years, selling 22 million commodities provided by 2 million Chinese online suppliers. In addition, DHGate.com has 20 million consumers from more than 200 countries and regions around the world, facilitating our access to sufficient and appropriate samples for investigation and enabling us to reasonably test our research hypotheses.

Over the course of our investigation, we first used a pilot survey to test whether the scale was understandable to the respondents and suitable for the CBEC environment. This was followed by the main survey. Participation in the main survey investigation was entirely voluntary and anonymous. We invited individuals to participate in the survey by sending a pop-up invitation message on the site. Consumers (i.e., respondents) were provided with three response options, "participate now", "do not ask again", or "maybe next time". There was no risk of loss regardless of whether respondents chose to participate. The entire investigation period spanned one month (from January 22, 2019 to February 28, 2019). In order to ensure that the respondents met the requirements of the survey objective, we did not consider the "no CBEC shopping experience" responses. Moreover, we dropped responses exhibiting obvious response patterns, such as those rating all items the same, as well as those with large amounts of missing values. In total, 515 respondents participated in the survey and 503 responses were usable. In addition, we excluded the responses that were not from one of the four regions (North America, Europe, Latin America and Oceania). Finally, we obtained an effective sample of 476 responses. For those items with few missing values in 476 responses, we used the series mean method to replace the missing values.

The respondents' personal information is shown in Table 1. According to Westland (2010), when the number (N) of respondents is more than 5 times the estimated parameter (p) of a model (i.e., N:p>5:1), the stability of the correlation matrix and the reliability of the analysis results can be guaranteed. Our conceptual model estimates 13 parameters and the number of effective samples in each group is greater than 65 (see Table 1). Thus, the sample sizes of four groups are acceptable for MI testing.

Table 1. Respondents' characteristics

Demographics	Category	Frequency	Percentage
Gender	Male	253	53.2
	Female	223	46.8
Age	≤20	40	8.4
	21-30	134	28.2
	31-40	95	20.0
	41-50	103	21.6
	51-60	61	12.8
	≥61	43	9.0
Experience in CBEC	Less than one month	38	8.0
	One to three months	70	14.7
	Three to twelve months	118	24.8
	More than one year	250	52.5
Located region	North America	196	41.2
	Europe	135	28.4
	Latin America	75	15.7
	Oceania	70	14.7
Located country	America	142	29.8
	Australia	62	13.0
	Canada	54	11.3
	Britain	41	8.6
	France	24	5.0
	Brazil	23	4.8
	Italy	20	4.2
	Others	110	23.1

In addition, to ensure demographic similarities among the four groups, we performed chi-square tests on gender, age and experience with CBEC. The results for gender ($\chi^2(4)=5.62$, $p=0.23$), age ($\chi^2(4)=9.23$, $p=0.06$) and experience with CBEC ($\chi^2(4)=7.88$, $p=0.10$) show no significant differences in the demographic profiles of the four groups. Therefore, demographic differences among the groups did not have a substantial impact on the MI test.

Descriptive results for the six measurement items are shown in Table 2 for each of the four regions. We conducted a Kruskal-Wallis H test to examine differences in the distributions of each item across the four groups. The results show no significant differences in the distributions of each item among the four groups, although the means are lowest in Oceania across all scale items, and highest in Latin America except for PD3.

Table 2. Detailed descriptive statistics of items in every region

Items	Statisitical indicators	North America	Europe	Latin America	Oceania	Kruskal-Wallis H test
PA1	Mean	4.15	4.10	4.30	3.65	$\chi^2(3)=5.21$, $p=0.15$
	Standard deviation	1.13	0.96	0.91	1.69	
	Skewness	-1.18	-0.86	-1.27	-0.37	
	Kurtosis	0.81	-0.07	1.39	-1.16	
PA2	Mean	4.03	3.98	4.26	3.74	$\chi^2(3)=4.75$, $p=0.19$
	Standard deviation	1.27	0.91	0.85	1.47	
	Skewness	-1.03	-0.79	-0.89	-0.45	
	Kurtosis	0.36	0.24	-0.38	-0.72	
PA3	Mean	4.18	3.99	4.28	3.74	$\chi^2(3)=7.45$, $p=0.06$
	Standard deviation	1.09	1.05	0.81	1.38	
	Skewness	-1.35	-0.96	-0.78	-0.36	
	Kurtosis	1.46	0.53	-0.84	-0.61	
PD1	Mean	4.01	3.79	4.17	3.70	$\chi^2(3)=4.70$, $p=0.20$
	Standard deviation	1.02	1.38	0.93	1.77	
	Skewness	-0.78	-0.73	-0.97	-0.53	
	Kurtosis	-0.09	-0.32	-0.02	-1.14	
PD2	Mean	4.05	3.77	4.19	3.74	$\chi^2(3)=7.06$, $p=0.07$
	Standard deviation	0.94	1.26	0.85	1.84	
	Skewness	-0.88	-0.62	-0.92	-0.56	
	Kurtosis	0.31	-0.41	-0.06	-1.19	
PD3	Mean	5.39	5.31	5.17	4.70	$\chi^2(3)=4.89$, $p=0.18$
	Standard deviation	1.04	1.02	1.10	1.40	
	Skewness	-0.44	-0.23	-0.09	0.24	
	Kurtosis	-1.10	-1.32	-1.43	-1.48	

Note: PA1, PA2 and PA3 are in the PA scale; PD1, PD2 and PD3 are from PD scale.

DATA ANALYSIS AND RESULTS

Reliability and Validity Test

Using pooled data for the studied regions, we carried out an exploratory factor analysis and calculated a KMO value of 0.773, suggesting that the data used in this study are suitable for exploratory factor analysis (Zhu, Yan, & Ding, 2020). Two factors were extracted and account for 81.852% of the total variance. According to the results given in Table 3, the factor loading of each item is greater than 0.7, meaning that each item shows a strong correlation with its factors (Baradaran, Farokhi, & Ahamdi, 2018).

For the reliability test, Table 3 shows the Cronbach α value and Composite Factor Reliability (CFR) value. Both values of each factor are greater than 0.7, showing that the scale used in this study is reliable (Wu, Ding, Xu, Mo, & Jin, 2016).

Table 3. Statistical results of some indicators

Factors	Items	Loadings	AVE	CR	Cronbach α
PD	PD1	0.879	0.742	0.896	0.864
	PD2	0.895			
	PD3	0.808			
PA	PA1	0.870	0.778	0.913	0.897
	PA2	0.901			
	PA3	0.875			

For the test of convergent validity, Table 3 shows that the convergent validity of the scale is acceptable, as the average variance extracted (AVE) for each factor is greater than 0.5 (Zhu et al., 2020). For the test of discriminant validity, the square roots of AVE values are 0.861 and 0.882 for the two scales, and the correlation coefficient between the two factors is 0.546, showing that discriminant validity is satisfied.

Homogeneity Test

In this study, when obtaining the geographical attributes of consumers, we measured the countries from which they came. However, according to the research of Zhu et al. (2019) and Mou et al. (2019), due to language, culture, habits and other factors, consumers' in the same countries and regions may have different perceptions. Therefore, before the formal MI test, we conducted a homogeneity test within each continent to test whether consumers on the same continent have invariant product description and product awareness. After the analysis of variance, the F-test results showed that consumers in the same continent had invariant perception of the six items related to product description and product awareness. We therefore focus our MI test on comparing continents.

MI Test

We tested the MI using Lisrel 8.7 software. In addition, four fit indices (χ^2, *NNFI*, *CFI* and *RMSEA*) were selected to evaluate the goodness of fit of the MI test. These four indicators are effective to use to analyze differences between nested tests (Chen, 2007).

Following the previously outlined MI test procedures, we first examined the fit of the two-factor product information measurement model for the four sample groups (Table 4). The result shows that the data for North America, Europe and Latin America fit the two-factor product information measurement model while those for Oceania do not. Considering our small sample from Oceania, this fit result is also acceptable. We then obtained invariance results of product information for CBEC consumers from North America, Europe, Latin America and Oceania (Table 5). Table 5 shows that the test probability of H_1 is $p<0.001$, showing that the four groups are not completely invariant. Therefore, our analysis proceeds to measure the level of MI among the four groups. According to our test of H_2, all other indicators are acceptable except for *RMSEA*. Considering differences between the effective samples of each group, the goodness of fit of H_2 is acceptable and meets the requirements of this test (Vandenberg & Lance, 2000). In the subsequent test, the chi-square difference between H_3 and H_4 reached the significance level ($p<0.001$), denoting different correlation coefficients between the two product information factors across the four groups. At this point, the MI test was terminated. In this test, H_2 and H_3 were satisfied, but H_1 and H_4 were not. The correlation coefficient of each group and comparisons of correlations for the four groups are shown in Table 6. We can see that the correlation coefficient for the sample from Oceania is significantly different from those of the other groups.

Table 4. Summary of model fit indices for two-factor product information measurement model

Two-factor measurement model	χ^2	*df*	*NNFI*	*CFI*	*RMSEA*	*SRMR*
North America *n*=196	13.306	8	0.986	0.993	0.056	0.042
Europe *n*=135	12.048	8	0.980	0.989	0.057	0.040
Latin America *n*=75	15.012	8	0.943	0.974	0.078	0.049
Oceania *n*=70	18.581	8	0.897	0.945	0.128	0.055

Table 5. Invariance results among four groups

Hypothesis	Test contents	χ^2	*df*	*NNFI*	*CFI*	*RMSEA*	$\Delta\chi^2$	Δdf	*p*
H_1	$\sum^{(1)}=\ldots=\sum^{(4)}$	168.282	63	0.915	0.911	0.101	-	-	<0.001
H_2	$form^{(1)}=\ldots=form^{(4)}$	79.804	32	0.942	0.969	0.094	-	-	-
H_3	$\Lambda^{(1)}=\ldots=\Lambda^{(4)}$	97.031	44	0.951	0.964	0.090	17.227	12	0.141
H_4	$\varphi^{(1)}=\ldots=\varphi^{(4)}$	158.996	47	0.925	0.941	0.122	61.965	3	<0.001

Table 6. Unstandardized correlation coefficient of each group and comparison of correlations from four groups

Groups	Correlation coefficient (PD, PA)	Vs Europe	Vs Latin America	Vs Oceania
North America	0.424	z=0.486, p=0.314	z=1.478, p=0.070	z=-7.435, p<0.05
Europe	0.369	-	z=1.019, p=0.154	z=-7.394, p<0.05
Latin America	0.266	-	-	z=-7.413, p<0.05
Oceania	1.541	-	-	-

According to the recommendations of Vandenberg and Lance (2000), we explored the higher levels of MI found across the different groups based on H_3. Excluding the sample from Oceania, we found the other three groups to exhibit an invariance of correlation coefficients between the two factors. In other words, the other three groups satisfy H_4. We continued to analyze levels of MI across these three groups. From our test of H_5, we found no invariant factor variances among the three groups. Detailed results are shown in Table 7. In this test, H_2, H_3 and H_4 were satisfied, but H_1 and H_5 were not. The variance of each group is shown in Table 8. We find the variances of the Europe group to be considerably different from those of the other two groups.

We continued to explore the higher levels of MI across the different groups based on H_4. Finally, after our analysis, we found the North and Latin American to satisfy H_5. More importantly, after a further analysis, we observed the two groups to also pass the H_6 test. In other words, the two groups present invariant intercepts for all measurement items. However, the invariance in variance-covariance matrices of measurement errors across the two groups could not be found (p<0.001). Table 9 presents the full analysis results. In this test, H_2, H_3, H_4, H_5 and H_6 were satisfied, but H_1 and H_7 were not.

The MI test steps and results description of this study are summarized in Figure 3.

Table 7. Invariance results among three groups (North America, Europe, Latin America)

Hypothesis	Test contents	χ^2	*df*	*NNFI*	*CFI*	*RMSEA*	$\Delta\chi^2$	Δdf	*p*
H_1	$\sum^{(1)}=\ldots=\sum^{(3)}$	65.645	42	0.976	0.977	0.065	-	-	0.011
H_2	$form^{(1)}=\ldots=form^{(3)}$	42.070	24	0.971	0.984	0.075	-	-	-
H_3	$\Lambda^{(1)}=\ldots=\Lambda^{(3)}$	47.804	32	0.979	0.985	0.061	5.734	8	0.677
H_4	$\varphi^{(1)}=\ldots=\varphi^{(3)}$	49.360	34	0.979	0.984	0.058	1.556	2	0.459
H_5	$\Phi^{(1)}=\ldots=\Phi^{(3)}$	63.262	38	0.974	0.978	0.070	13.902	4	0.008

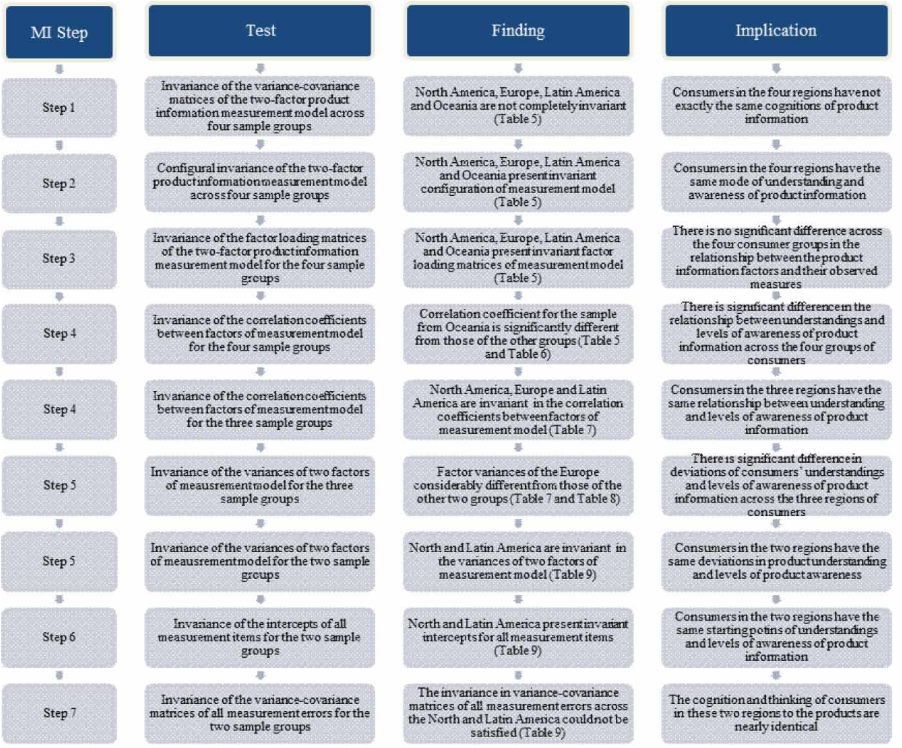
Table 8. Unstandardized factor variance estimates among three groups

Groups	Variance (PD)	Variance (PA)
North America	0.728	0.856
Europe	1.046	0.520
Latin America	0.654	0.771

Table 9. Invariance results between two groups (North America, Latin America)

Hypothesis	Test contents	χ^2	*df*	*NNFI*	*CFI*	*RMSEA*	$\Delta\chi^2$	Δdf	*p*
H_1	$\sum^{(1)}=\sum^{(2)}$	33.686	21	0.980	0.986	0.058	-	-	0.039
H_2	$form^{(1)}=form^{(2)}$	30.583	16	0.967	0.982	0.080	-	-	-
H_3	$\Lambda^{(1)}=\Lambda^{(2)}$	34.771	20	0.972	0.981	0.074	4.188	4	0.381
H_4	$\varphi^{(1)}=\varphi^{(2)}$	36.483	21	0.970	0.979	0.074	1.712	1	0.191
H_5	$\Phi^{(1)}=\Phi^{(2)}$	38.839	23	0.973	0.979	0.072	2.356	2	0.308
H_6	$\tau^{(1)}=\tau^{(2)}$	44.806	29	0.977	0.979	0.066	5.967	6	0.427
H_7	$\Theta^{(1)}=\Theta^{(2)}$	58.620	35	0.981	0.977	0.061	13.814	6	0.032

Figure 3. Test steps and findings description



Nonresponse Bias

Referring to the procedures of Armstrong and Overton (1977), and Gefen, Rigdon, and Straub (2011), we addressed the nonresponse bias by comparing the gender and age variables of the early respondents to those of the later respondents. As far as the 476 valid responses in this study were concerned, 264 were considered early-stage responses, and 212 responses were in the later stage. A chi-square test of the early and later responses showed that respondents did not differ significantly ($p>0.05$) in either gender or age. Therefore, this research excluded the possibility of nonresponse bias.

Common Method Bias

In this study, the common method biases were evaluated by Harman's single factor test. The results showed that the explanatory proportion of the largest variance factor was 32.11%, which indicated that there were no common method biases (Podsakoff & Organ, 1986). Moreover, we also used the marker variable method to test for common method bias (Chin, Thatcher, & Wright, 2012). The results of the data analysis showed that the marker variables (Williams, Hartman, & Cavazotte, 2010) had no significant influence on product description or product awareness. Therefore, common method bias was not a critical issue in this study.

DISCUSSION

This study analyzed invariance in product information for CBEC consumers around the world via an MG-CFA. Specifically, we explored invariance in self-reported understanding of product descriptions and levels of product awareness in relation to CBEC platforms among consumers in North America,

Europe, Latin America and Oceania and analyzed higher levels of invariance across regions. Three interesting and meaningful results are identified. First, product information exhibits MI in factor loading matrices across the four studied regions (i.e., it satisfies H_2 and H_3 but does not satisfy H_1 and H_4). This result shows that although CBEC has become a globalized commerce activity, for consumers from the four studied regions, there are certain similarities and differences in cognitions of product information given on CBEC platforms. The empirical analysis of this study shows that consumers on different continents, e.g. Oceania, have some different understandings of product information on CBEC platforms to others, e.g. Latin America. Although there are differences in cognitions about product information across the four groups of consumers, we find no significant difference in the variance in the measured variables explained by the two product information factors, i.e., the relationship between product description and product awareness and their underlying measures, as given by the factor loading matrices, are the same across the four groups. According to Fang et al. (2016), when factor loading matrices achieve cross-group invariance, MI is accepted. Therefore, on CBEC platforms, sellers do not need to worry that consumer understanding of product information needs to be measured differently due to differences in language, culture, habits, etc. When faced with the same product information, understanding and awareness of the product information by consumers in North America, Europe, Latin America and Oceania can all be observed in the same way.

Second, product information presents an MI of factor correlation coefficients for North America, Europe and Latin America (i.e., it satisfies H_2, H_3 and H_4, but does not satisfy H_1 and H_5). This result indicates that consumers from these three regions exhibit an invariant relationship between their product description understanding and their product awareness in CBEC environments, implying that consumers in these three regions cognize product information and link product description and awareness in a similar fashion. On the basis of this conclusion, for consumers in North America, Europe and Latin America, in addition to having the same understanding and awareness of products information, they can also correctly link these products with the impressions and knowledge of these products in their minds during CBEC activities. This links will help them form a series of follow-up activities about the product, such as emotions, behaviors and so forth.

Third, product information presents an MI for intercepts of all measurement items for North and Latin America (i.e., it satisfies H_2, H_3, H_4, H_5 and H_6 but does not satisfy H_1 and H_7). This result implies that the starting point of consumer product understanding and levels of product awareness across all of our survey questions is the same and that the scores of our scales can be directly analyzed without data preprocessing. This conclusion shows that consumers in North and Latin America have no significant difference in the impression and knowledge level of the linked products on CBEC platforms. This suggests that the cognition and thinking of consumers in these two regions to the products are nearly identical. Therefore, for consumers in these two regions, sellers can adopt a variety of marketing methods to promote products without fear of difference in these consumers' understandings.

We believe that the above three conclusions can be attributed to differences in behaviors among consumers in different regions. According to satisfaction theory (Kaminska, McCutcheon, & Billiet, 2010), due to access to limited opinions, wisdom, cognition, knowledge, skills, energy, time and other individual factors, ideal optimization decisions are often not achieved. In this sense, in practice, as long as objectives of decision-making and means of implementation meet the requirements of decision makers, they will make decisions and take action immediately. In a CBEC setting, after seeing a product, consumers will extract product information, determine whether to use this information, and then make a decision on further activities. The best decisions are made when consumers think carefully and adequately about each stage (Fang et al., 2014). However, on a CBEC platform, cognitive requirements for such optimization decisions often exceed the motivations or abilities of consumers. Therefore, in many cases, consumers seek convenient means to identify product information with less cognitive effort. Meanwhile, in the online environments, consumers may simultaneously engage in various activities such as listening to music, watching movies, chatting and playing online games, limiting attention allocated to shopping on CBEC platforms. All these behaviors will have an impact

on consumers' cognition of product information. In addition, according to social exchange theory, consumers always weigh the costs and benefits of their behaviors. On a CBEC platform, consumers are very susceptible to various influences, and deviations in their behaviors are illustrated by our analysis.

In addition, social desirability responses serve as an alternative explanation to the observed MI in product information across different regions. According to this theory (Fang et al., 2014), consumers' cognition of potential risks will affect their attitudes and willingness to participate in CBEC shopping. In our study, participating consumers from different regions had different educational, cultural and religious backgrounds and habits, to name a few. Thus, the kinds of risks that they cognized on CBEC platforms may have differed, which would have had some impact on our MI results.

IMPLICATIONS

The theoretical contribution of this study is mainly summarized in the following two aspects. First, compared to the results of analyzing product information from a single dimension such as Mou et al. (2020), we evaluate the MI of product information from the two dimensions of product description and product awareness. Product information is a concept involving several activities of consumers. From the perspectives of product description and product awareness, we can comprehensively analyze the similarities and differences of consumers' thinking and cognition of product information on CBEC platforms, which is conducive to obtaining more profound research conclusions. Moreover, in view of these two dimensions, this study applies a two-factor model to carry out analysis. Based on the results of this model, researchers can conduct MI of complex models related to product information in CBEC. Second, compared to the study of Fang et al. (2016), which did not test the MI of correlation coefficients between factors, this study specially tests the MI of this content. Our findings prove that this test step is necessary. Specifically, our results show that product information exhibits invariance in factor loading matrices for North America, Europe, Latin America and Oceania (i.e., it satisfies H_3), but does not meet the MI of correlation coefficients between factors (i.e., it does not satisfy H_4); while product information exhibits invariance in correlation coefficients for North America, Europe and Latin America (i.e., it satisfies H_4), but does not meet the MI of variance-covariance matrices between factors (i.e., it does not satisfy H_5). In other words, if we do not test the MI of correlation coefficients between factors, we will not find the differences between the MI among four regions and the MI among three regions. However, these two test results are actually different. Therefore, the test of the MI of correlation coefficients between factors should not be ignored in a CBEC environment.

The conclusions of this study have a number of management implications for sellers on CBEC platforms. Sellers should apply targeted information presentation strategies and methods for consumers in different regions to meet marketing requirements. On one hand, according to our finding of invariant product understanding and product awareness among consumers across four regions, sellers could publish product information that is clear and attractive and that most consumers can fully understand. In this case, sellers must focus on the clarity and simplicity of product information. On the other hand, our findings show that consumers in North and Latin America exhibit almost the same levels of product understanding and awareness. Therefore, for consumers in these two regions, sellers can specially design personalized product information and comprehensively display products through the use of videos, photos, diagrams and so forth to attract consumer attention and promote purchasing behavior.

LIMITATIONS AND FUTURE RESEARCH

This study is mainly limited in that data were collected from a single CBEC platform used in China. And, the number of valid samples for the study is relatively small, especially for data from Latin America and Oceania. Researchers may collect large sample data from multiple CBEC platforms in future research to draw more novel and valuable conclusions. Furthermore, in this study we only constructed a two-factor model of product description and product awareness. Future research can

add other variables related to product cognition (e.g., product evaluation, product conviction) into the analysis model to obtain other novel conclusions. In addition, we only analyzed invariance in product information among consumers across regions in a CBEC setting. Consumers' cognitions of product information can be analyzed and explored across cultures or countries and researchers are in turn encouraged to conduct further analyses and evaluations in this area. Lastly, the product itself may also have a certain degree of influence on the global consumers' cognitions of product information. Scholars can carry out further analysis of this issue in the future.

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