INSTITUTO
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Determinants of Purchasing Online Courses through Education Platform in China

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Doctor of Management

Supervisors:
PhD José Paulo Esperança, Professor,
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Abstract

Online courses have become the main source of income for online education platforms. It is of great value to explore the factors affecting users' intention to buy online courses. Based on the technology acceptance model, perceived value theory and perceived risk theory, this study constructs the structural equation model of the purchase intention of online courses by taking users on online education platforms as the research object, and resorts PLS-SEM for analysis. This research explores factors that impact the intention to buy online courses and levels of these impact. The research questionnaire of this study was developed through literature review, and 669 valid questionnaires were collected. Data analysis was performed using IBM SPSS V24.0 and SmartPLS 3.2.8.

Before the multi-group analysis, it is found that perceived value, time and space autonomy, course free trail exert positive impact on purchase intention, while perceived risk has negative impact on it. Perceived cost does not significantly affect purchase intention. Time and space autonomy, perceived usefulness, and perceived ease of use are positively affecting perceived value, while perceived cost and perceived risk negatively affect perceived value. Course free trail does not significantly affect perceived value. Perceived value completely mediates perceived cost, and partially mediates the impact of time and space autonomy and perceived risk on purchase intention. Word-of-mouth positively moderates the impact of perceived value on purchase intention. Age has negative impact on purchase intention, while education positively affects purchase intention. Perceived profit (perceived ease of use, perceived usefulness, time and space autonomy) significantly and positively affects perceived value, and perceived loss (perceived cost, perceived risk) significantly and negatively affects perceived value. Perceived value mediates the impact of perceived gain and perceived loss on the users' purchase intention.

PLS multi-group analysis is conducted according to the users' experience in buying a course. Users with different purchasing experience have different significance in terms of course free trail, perceived risk, perceived ease of use, time and space autonomy, and education.

Based on the data analysis, this study also discussed the corresponding recommendations, such as guaranteeing course quality, providing word-of-mouth, grouping users according to their purchasing experience, using artificial intelligence to recommend online courses for users; optimizing functions of time and space autonomy, improving user experience with 5G, virtual reality, and augmented reality; reducing course price with cloud services and big data technologies, and providing more course free trial in an attempt to reduce users' perceived risk.

Keywords: online courses; online education platforms; purchase intention; perceived value

JEL: L81; D83

Resumo

Os cursos à distância tornaram-se a principal fonte de rendimento para as plataformas de educação online. O estudo dos fatores que afetam a intenção dos utilizadores de compra de cursos online tem uma grande valia. Com base no modelo de aceitação de tecnologia, na teoria do valor percebido e na teoria do risco percebido, este estudo constrói o modelo de equações estruturais da intenção de compra de curso online ao considerar os utilizadores de plataformas de educação online como objeto de investigação, com base na metodologia PLS-SEM (mínimos quadrados parciais – modelação com equações estruturais). Esta pesquisa explora fatores que influenciam a intenção de compra de cursos e os seus níveis de impacto. O questionário de investigação deste estudo foi desenvolvido através da revisão da literatura e foram recolhidos 669 questionários válidos. A análise de dados foi realizada utilizando o IBM SPSS V24.0 e o SmartPLS 3.2.8.

Antes da análise multi grupos, verificou-se que as variáveis valor percebido, autonomia de espaço e tempo e teste gratuito de curso exercem um impacto positivo na intenção de compra, enquanto o risco percebido tem um impacto negativo sobre o mesmo. O custo percebido não afeta significativamente a intenção de compra. Autonomia de espaço e tempo, utilidade percebida e perceção de facilidade de utilização afetando positivamente o valor percebido, enquanto custo percebido e risco percebido afetam negativamente o valor percebido. O teste gratuito do curso não afeta negativamente o valor percebido. O valor percebido é um mediador integral do custo percebido, e mediador parcial do impacto da autonomia de espaço e tempo, risco percebido na intenção de compra. Palavra-de-boca (word of mouth) modera positivamente o impacto do valor percebido na intenção de compra. A idade tem um impacto negativo na intenção de compra, enquanto a educação afeta-a positivamente. O lucro percebido (facilidade percebida de utilização, utilidade percebida, autonomia de espaço e tempo) afeta significativa e positivamente o valor percebido, e a perda percebida (custo percebido, risco percebido) afeta significativa e negativamente o valor percebido. O valor percebido é mediador do impacto do lucro percebido e da perda percebida na intenção de compra dos utilizadores.

A análise de vários grupos da análise PLS foi realizada de acordo com a experiência dos utilizadores na compra de um curso. Os utilizadores com diferentes experiências de compra têm uma significância diferente em termos de experimentação gratuita dos cursos, risco percebido, facilidade percebida de utilização, autonomia de espaço e tempo e educação.

Com base na análise de dados, este estudo também analisou as recomendações correspondentes, como garantir a qualidade do curso, fornecer informações de word of mouth, agrupar os utilizadores de acordo com a sua experiência de compra, utilizando a inteligência artificial para recomendar cursos online para os utilizadores; otimizar funções da autonomia de espaço e tempo, melhorar a experiência do utilizador com 5G, realidade virtual e realidade aumentada; reduzir o preço do curso com serviços na nuvem e tecnologias de grandes bases de dados, e fornecer mais cursos experimentais gratuitos para tentar reduzir o risco percebido dos utilizadores.

Palavras-chave: curso online; plataformas de educação online; intenção de compra; valor percebido

JEL: L81; D83

摘要

在线课程成为在线教育平台的主要收入来源，开展对在线教育平台用户课程购买意愿影响因素的探讨有着重要的意义。本文以用户感知风险理论、信息系统中的技术接受模型和用户感知价值理论作为本研究的理论基础，将在线教育平台用户列为研究的对象，构建了在线课程购买意愿的结构方程模型，采用了 PLS-SEM 来探索影响用户课程购买意愿的因素及其作用程度。通过对以往大量文献仔细回顾开发了本次研究的调研问卷，共收到 669 份有效的问卷，分别运行 IBM SPSS V24.0 数据分析软件和 SmartPLS 3.2.8 数据分析软件进行之后的数据分析。

在未进行多群组分析中发现：用户感知价值、时空自主性、课程免费试听正向且显著的影响用户对在线课程购买意愿;用户的感知风险负向且显著的影响了用户课程购买意愿;用户感知成本却未显著的影响用户对在线购买意愿;用户感知有用性、用户感知易用性、时空自主性都正向且显著影响研究模型中的感知价值;而其中用户感知成本、用户感知风险都表现为负向且显著影响了用户的感知价值;其中课程免费试听对感知价值无显著影响;感知价值完全中介了感知成本，部分中介了用户感知风险和时空自主性对用户课程购买意愿的相关影响;课程口碑存在着正向的调节了用户感知价值对课程购买意愿的作用影响，年龄负向影响课程购买意愿，教育正向影响课程购买意愿。用户的感知利得(用户感知易用性、用户感知有用性、时空自主性)皆正向且显著的影响了用户感知价值，用户的感知利失(用户的感知成本、用户的感知风险)都负向且显著的影响用户感知价值，其中感知价值则中介了用户在感知利得与感知利失两方面对用户课程购买意愿的影响。

根据用户的课程购买经验进行了 PLS 多群组分析，不同购买经验的用户在课程免费试听、感知风险、感知易用性、时空自主性、用户教育拥有不同的显著性。

本研究在数据分析的基础上还进行了相应的讨论并给出了对应的建议。

关键词：在线课程；在线教育平台；购买意愿；感知价值

JEL: L81; D83

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List of Acronym

AR	augmented reality
CFT	course free trial
CINIC	China Internet Network Information Center
CPV	customer perceived value
FIRI	Foresight Industry Research Institute
OEI	online education industry
OEP	online education platform
PC	perceived cost
PEU	perceived ease of use
PI	purchase intention
PR	perceived risk
PU	perceived usefulness
PV	perceived value
TAM	technology acceptance model
TRI	Tencent Research Institute
TSA	time and space autonomy
VR	virtual reality

WM	word-of-mouth

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Chapter 1: Introduction

1.1 Research background

China Internet Network Information Center (CINIC, 2019) conducted a survey which illustrated that the number of Internet users in China reached 829 million by the end of December 2018, of which users of online education reached 201 million, an increase of 46.05 million compared with the figure in 2017. The annual growth rate was 29.7%. The number of users using online education through mobile phones was 194 million, an increase of 63.3% compared with the figure in 2017. Users of mobile online education in China set a record high, and online education users further concentrated on using mobile phones and mobile terminals.

The People's Bank of China (2019) argued that financial institutions in China's banking sector handled a total of 220.132 billion non-cash businesses, totaling 3,686.67 trillion yuan in 2018, of which the number of mobile payment services reached 60.51 billion, at a total amount of 277.39 trillion yuan, an increase of 61.19% and 36.99% respectively. The scale and growth of online payment is still of great momentum, reflecting that China's online payment has been widely popularized and accepted by users.

China's Ministry of Industry and Information Technology and the National Development and Reform Commission (2018) jointly pointed out that the scale of China's information consumption shows a clear growing trend. By 2020, China's information consumption is expected to reach 6 trillion yuan, with an average annual growth rate of at least 11%. The promotion of information technology is obvious, and the output value of related sectors is expected to reach 15 trillion yuan. The government encourages the development of Internet culture, Internet medicine and other fields. The rapid development of Internet technology, the large-scale popularization of smart terminals, and the comprehensive penetration of mobile application services are revolutionizing people's habits of shopping, entertainment, travel, and knowledge acquisition. The traditional industry can also harness advantages of the advantages of the Internet to be better integrated with the Internet industries. At present, the online education platform (OEP) is an important communication channel for Chinese people to obtain information and knowledge. These platforms aim at using application technologies of the Internet and mobile Internet to provide online and mobile learning services to the public, breaking the limits brought by traditional education models and becoming a new type of business mode.

In recent years, with the growing support of the state for online education and the increasing acceptance of online learning methods, Tencent Research Institute (TRI, 2019) found that 96% of users choose B2B2C OEP with relative decent scale and branding. The scale of B2B2C OEP users has grown rapidly. According to iResearch (2018), the online education market in China reached 194.12 billion yuan in 2017, an increase of 22.9% on the previous year. E-commerce Research Center of Internet Economy Institute (ERCIEI, 2019) reported that the market size of China's online education industry (OEI) has exceeded 300 billion in 2018, which is 45% larger than that in 2017. The vast market is attracting many traditional educational institutions and Internet companies to accelerate their process of online education deployment. With the increasing demand for online education courses in the fields of education for children, K12, higher education, vocational education, etc., the online education curriculum market is continuously segmented, and the curriculum service model of online education presents a diversified trend. At present, from the perspective of business, the domestic online education market can be divided into: comprehensive platform (e.g., Tencent Classroom, Taobao Education, Baidu Teaching), language learning (e.g., 91 foreign teachers, 51 talk), early childhood education (e.g., 61 Time Network, Beva Network), K12 education (e.g., Xueersi Network School), consultation of studying abroad (e.g., Huatuo Network School), vocational education and skills enhancement (e.g., Dube.com, Baidu Chuanxun), exam and training (e.g., Highso, Huanqiu Network School), e-learning tools (e.g., YY voice, dictionary), audio and video knowledge (e.g., Himalaya FM, Litchi FM). The diversification of new demands of Internet knowledge users has driven the online education market to be more segmented, the industry scale has continued to grow, and the prospects in many sub-sectors are promising.

However, while the OEI is welcoming the prosperity, it also indicates that the competition between OEP companies is becoming increasingly fierce. With the intervention of Internet giants such as Baidu, Tencent, and Alibaba, the online education market has ushered in a battle for intensified competition. The homogenization of products and services in the OEI and the low purchase rate are becoming more prominent.

Ni (2018) published an article, mentioning that VIPKID, an online English education platform for children, which was founded nearly four years ago, received 500 million dollar at its round of financing on June 21, 2018, the largest one in the global OEI to date. In July 2018, Hyphen Education announced the completion of its third round of financing, and Zuoye Bang completed its fourth funding round at 350 million dollars. New Oriental Education, Hujiang Net School and many other pace setters of the OEP were submitting their IPO prospectus. In addition, it is said that one of the Internet unicorns, Today’s Headlines, intended to touch the water of OEI through the acquisition of an OEP called “Xue Ba 100”. The investment and financing situation seems a hot streak. However, most online education companies are facing losses. Through the IPO prospectus of Hujiang Net School, and financial statements of Suntech and 51talk in 2018, it is known that all the above companies had a net loss. According to the survey conducted by Internet Education Research Institute (2016) on business operation of 400 OEPs, results showed that 70.58% were making losses, with 13.24% in break-even and only 16.18% making a profit. The overall profitability of start-up projects of online education is expected to be less than 5%, with a failure rate of about 15% and a loss rate of 70%. It can be seen that most OEP companies do not have a clear profit model, and the phenomenon of burning money is serious. Therefore, it is urgent to explore effective profit methods in this industry. For some online education service providers who started earlier and have a larger scale, it is also an urgent need to explore new business models and how to achieve user realization after the accumulation of original users. At present, the profit model of China’s B2B2C OEPs mainly rely on course fees, online learning service fees, software fees, platform commissions and advertising revenue. Among them, providing high-quality learning content and cultivating more paid users is the the key to the profit model of the majority of large-scale OEPs. The Institute of Journalism and Communication of the Chinese Academy of Social Sciences (IJCCAS, 2018) pointed out that the number of users in the knowledge-paid market continued to expand from

93 million in 2016 to 188 million in 2017, with an annual growth rate of 102.2%, reflecting the willingness of users to pay for high-quality knowledge content and it is feasible to cultivate knowledge-paid model for profitability on the OEP. However, how to persuade users to pay for content or services needs innovative strategies.

In summary, thanks to the mature development of Internet technology and its application services, online education has become a universally accepted method of learning and a trend in the development of digitized education. Nowadays, the user scale and industry scale of the B2B2C OEP are still growing rapidly. The OEI has promising market prospects and became an emerging industry that is widely acknowledged. However, the rapid growth of the B2B2C OEP has not brought more revenue to the platforms. Instead, it has increased the burden on the platforms, at higher expenses on servers, development and personnel maintenance. Foresight Industry Research Institute (FIRI, 2019) reported that the course purchase ratio on OEP is not high, resulting in many platforms unable to make ends meet. How to recognize the relevant factors that impact purchase intention (PI) of online courses, grasp the user's needs, and improve the user's PI and purchase rate become urgent problems that B2B2C OEP needs to solve.

Purchase intention (PI) is the possibility that a user purchases a particular product or brand and is proven to be an important indicator to predict consumer behavior (Feng, Mu, & Fu, 2006). Many e-commerce researches show that users' PI is an important indicator for participating in e-commerce transactions. Based on the previous studies, PI in this study refers to the subjective willingness of users to purchase online courses on B2B2C OEPs. In this context, this study deemed users on commercial B2B2C OEP as the research object, explore the intention to purchase online education courses from the perspective of perceived value (PV), identify factors that impact users' PI on B2B2C OEP, and analyze the extend of impacts of the above-mentioned factors through theoretical analysis and empirical study, in order to deliver strategic benefits for the commercial operation of B2B2C OEPs, and improve their profitability.

1.2 Research problems

Nowadays, with the increasing acceptance of the online learning method and the rapid growth of online education users, OEI has a huge market potential, attracting many investors and entrepreneurs to join in the search of wealth. However, most OEPs are still in the stage of burning money, and the unclear business model is a key issue holding many platforms from sustainable development. Currently, the main probability models for OEPs are charging through paid content, online learning service fees, software fees, platform commissions and advertising revenue. Among them, the paid online course is a profit model with great market potential for B2B2C OEP in the future, which is also the key to achieve user realization and sustainable development. While competing for user resources and occupying market share, some of the relatively mature commercial OEPs, such as Tencent Classroom, Taobao Education, Baidu Lectures, etc. are also gradually exploring and improving the business model of paid courses and paid services.

Li (2016) argued that the use of "free" Internet services has become a common consensus among Chinese netizens in the context of China's Internet advancement. However, for OEPs, how to improve their users' intention to purchase so as to generate more income has become an urgent issue for these platforms. The online course on OEP is regarded as a commodity according to the existing researches, but rare researches adopt the perspective of commodity and individual consumption behavior to study users' intention to purchase courses on OEP. Xu, Zhang, and Dong (2018) considered that finding factors that exerts impacts on users' intention to purchase courses can help online course providers access to a greater number of users in the era of information explosion. Chen, Jiao, and Li (2019) found that paid knowledge is gradually being accepted as a new business model, indicating that it is a practical business model that users pay for knowledge and courses. Therefore, the cultivation and fostering of users' PI has become the key to the profitability and business model of OEPs.

The industry of OEP urgently needs more research to fill these gaps, so that enterprises can have a deeper understanding of their users' PI, helping the business enterprises to adjust their business strategies in a targeted manner, and at the same time enhance their own competitiveness and strive for larger market share. Therefore, the following research questions have been covered in this study:

(1) Identifying the leading factors of users' intention to purchase online courses.

(2) Researching on the role of PV in mediating the impacts of PI on OEP.

(3) Analyzing the impacts of the factors related to users' intention to purchase online courses on B2B2C OEPs.

1.3 Research objectives

The research objectives of this study are as follows:

1. Under the background of the OEP in China, revealing the relevant factors that affect users' intention to purchase online courses.

2. After revealing the factors affecting the purchase of OEP users, determining the key factors and impacts of the factors that affect users' intention to purchase online courses.

3. Provide valuable reference and suggestions for enterprises in OEI in terms of formulating business strategy, product development strategy, marketing plan, etc., and providing effective decision-making reference for improving the conversion rate of potential users' purchasing online education products, so that OEPs can master purchasing behaviors of their consumers in China's e-commerce environment, thus better responding to complex and volatile market conditions, promoting sustainable development and forming new competitive advantages for corporate by implementing accurate solutions to customer needs.

1.4 Research methods

Based on the basic research of management, economics, psychology and sociology, comprehensive and in-depth research was carried out combining qualitative research and quantitative research. The research objectives are achieved through the effective combination of normative research and empirical research. The main research methods of this study are as follows:

(1) Literature investigation and content analysis

Through the collation of relevant literature and data, determining various factors that impose impacts on users' intention to purchase on OEP, analyzing and summarizing the structural variables in the model and then constructing a theoretical model of factors impacting online PI of consumers, and determining the research objectives and hypotheses, to further determining specific measurement indicators of structural variables in the theoretical model.

(2) Questionnaire survey

Based on mature scales at home and abroad, items in the questionnaire were selected through advice from experts, and the questionnaire was designed based on the characteristics and research hypotheses of B2B2C OEPs in China. In order to ensure the validity of the questionnaire, potential variables and measurement items in this study were derived from or referenced by existing literature. In addition to that, the structure and content of the initial questionnaire were further adjusted through the pre-investigation.

Samples for empirical analysis were obtained through questionnaire survey. After the preliminary design, the questionnaire was released via an online tool to issue questionnaire, Questionnaire Star. The number of questionnaires issued to its users exceeded 26.8 million in 2018 and the number of questionnaires collected on this platform exceeded 1.77 billion since it was launched online in 2006 (Questionnaire Star, 2018).

This study includes a pre-investigation to test the reliability and validity of the items, and then make further analysis of the items after drawing the conclusion. The first pre-investigation invited users with experience in the OEP to conduct surveys through the WeChat platform, in order to ensure that the respondents can understand the meaning of the measurement items and accurately fill in the formal investigation. Then, the study provided carefully modified items with ambiguous meanings and wordings according to feedback of these respondents. The first pre-investigation was the premises of a large-scale formal investigation later where only users with relevant experience in using online courses are eligible to participate in the survey. The questionnaire respondents were consisted of two parts. On the one hand, the questionnaire was available to all users on the Questionnaire Star. Users can participate in the survey without any invitation. On the other hand, the study was based on randomly selected respondents via sending invitations through QQ group, WeChat group and email.

Finally, the revised questionnaire was distributed and collected through multiple channels of OEP in an electronic format. Users of B2B2C OEP were invited to fill out the questionnaire and raw data were collated and analyzed.

(3) Descriptive statistical analysis

After obtaining the sample data needed for sending the questionnaire, statistical software was used to perform descriptive statistical analysis to understand the structure and distribution of the samples, so as to grasp the basic statistical characteristics of the data.

(4) Reliability and validity analysis

Reliability and validity analysis were conducted to evaluate the quality of the questionnaire. The stability and consistency of the questionnaire to test related variables were measured by reliability analysis, and the validity of the questionnaire was tested by factor analysis.

(5) Empirical analysis (PLS-SEM)

This study adopted statistical analysis software, SPSS and SmartPLS, for comprehensive analysis. Descriptive statistical analysis could be performed using SPSS, while SmartPLS could not only analyze the reliability and validity of structural equation modeling (SEM) model, but also test hypotheses.

1.5 Research framework

1.5.1 Research path

This study starts with an extensive review of the literature, including the research background of online education development in China. The market size, service providers and potential users of online education all show a clear upward trend. However, many OEPs suffer losses and a decreasing number of users. The intention to purchase the course is not high.

Therefore, it is necessary to carry out research on identifying factors impacting the intention to purchase online courses of users on OEP and the degree of impacts of these factors, in order to find ways to improve users' PI. This is also the commercialization goal for OEPs to increase their income. These act as the foundation for he to study factors imposing impacts on users' intention to purchase courses on OEP. Based on the existing literature and reviewing relevant theories, theories about PV and perceived risk (PR), a theoretical model was constructed, and relevant research hypotheses are proposed. The hypotheses are tested through questionnaire survey and empirical analysis. Finally, the results reveal factors imposing impacts on users' intention to purchase courses on OEP. The author explains contributions and limitations of the research and proposes direction for future research. The research path taken is shown in Figure 1-1.

1.5.2 Chapter arrangement

This study takes users' intention to purchase courses on OEP as the research object, focusing on the perspective of PV. Against the background of B2B2C OEP, and based on the PV, online courses on B2B2C OEP are regarded as network virtual goods. Situational variables including word-of-mouth (WM), perceived ease of use (PEU) that impact users' purchase behavior is selected in combination with the scene of selling virtual goods in e-commerce. A total of six chapters are arranged for thesis writing. The main research contents are as follows:

The introduction includes a detailed description of the launch of this study. Firstly, under the background of the rapid development of Internet in China and the continuous growth of the online education market, most OEPs have a common outstanding problem, operating loss. Then from the research background, the main research questions of this thesis are proposed, and the research purposes of this research are described. The research methods and the frameworks used in this study are depicted, and the implementation of this research is explained. Finally, the theoretical and practical value of this research are expounded, and the innovation and contribution of this research are extracted accordingly.

Chapter three provides an overview of the B2B2C OEI, to study factors that exert impacts on online PI. The B2B2C OEP as a professional e-commerce website should also have the characteristics of the OEP. Therefore, this chapter defines the business model of online education in China, reclassifies the OEP, defines the B2B2C OEP, sorts out its characteristic and describes its development source and future trends.

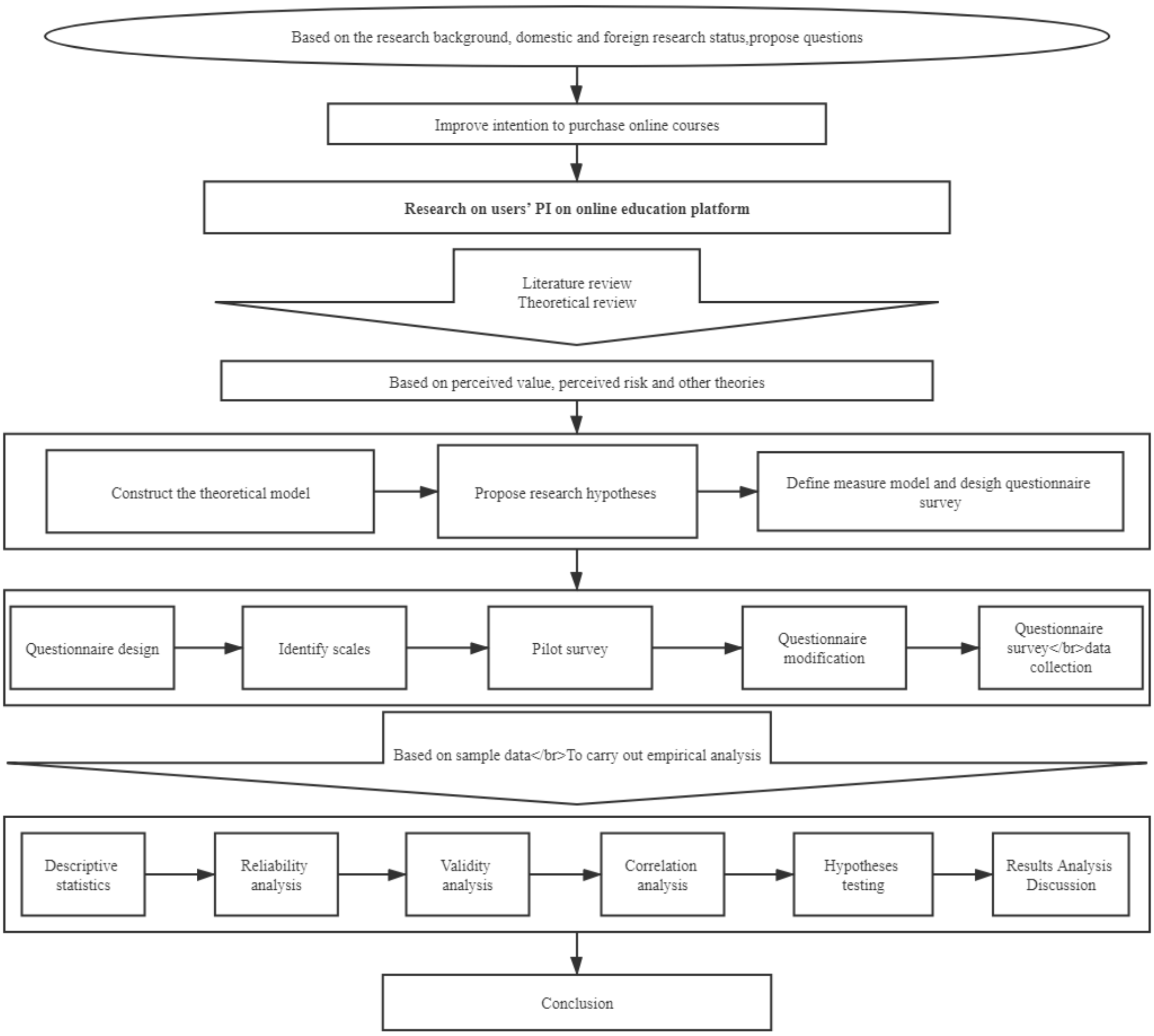

Figure 1-1 Research path

Chapter four covers the research design and data collection. Through the summary of relevant theoretical literature, based on the existing research as a foundation and related theories, combined with the research objectives and his point of view, a theoretical model of users' intention to purchase courses on B2B2C OEP that takes WM as the moderator of PV is constructed. Through researching on the mutual impacts of each variable in the model, research hypotheses are put forward accordingly, and the research model with perceptual value as the mediator is constructed. In order to ensure the reliability and validity of the questionnaires and variables used in this study, the questionnaire used in the study adopts mature scales that have been verified for multiple times. First, the scales are designed targeted for the variables involved in the model, and then the questionnaire is designed. The author also utilized pre-investigation to test the reliability and validity of the questionnaire and optimize the items. Finally, after deleting the unreasonable items, the final version of questionnaire is ready to distribute, and after collecting answers to the questionnaire, the collected data are effectively organized and arranged.

Chapter five focuses on data processing and analysis, testing the research hypotheses proposed in this study. After the questionnaire was collected, descriptive statistical analysis was carried out, and the reliability and validity of the items to measure the construct variables are tested, after which the path analysis and moderating effect analysis of the research model are performed. Finally, the results can reveal the key factors affecting consumer behavior and their impacts degree.

Chapter six summarizes the conclusions and paths for further research. This chapter is based on the results of theoretical research and empirical analysis, sorting out the results and findings of this research, proposing recommendations for the OEP, explaining the inadequacy and limitation of the study and providing direction and a certain degree of assistance for further research in the direction of online education.

1.6 Research value and contribution

1.6.1 Realistic value

1. For the OEI: deeply analyzing the main sources of income for online education, allowing investors, entrepreneurs, companies and other institutions to understand the business model, triggering their interest to participate, and calling for more social forces to participate in the development of the OEI so as to promote the development of China's OEI.

2. For enterprises: revealing the realization process of users' PI on OEP, providing valuable

reference and suggestions for enterprises in the OEI to formulate business strategies, product development strategies, marketing plans, etc., offering an effective basis for decision making to enhance the purchase conversion rates of their potential users, enabling OEP companies to grasp the characteristics of consumers' purchasing behavior in China's e-commerce environment to cope with complex and volatile market conditions, and promoting sustainable development and forming new competition advantage by understanding customer real needs and implementing correct solutions.

3. For product marketing: providing reference for companies in this industry to better implement marketing strategies. Studying the factors that imposing impacts on PI on online education courses helps enterprises to develop appropriate marketing strategies for customers, reduce blind marketing expenditures, and promote the development of China's OEI.

1.6.2 Theoretical value

1. The research object focuses on the commercial OEP. Previous scholars paid more attention to the analysis of factors impacting user behavior in the context of MOOC and self-built online learning systems, but less on the usage scenarios of the commercial OEP. Nowadays, the development trend of online education has shown a good momentum and has become a hot spot for the business and education sectors. The OEP for commercial operation is more dynamic and sustainable. Therefore, this thesis analyzes factors that impact users' purchasing behavior through empirical analysis, which has a positive effect on breaking through the limitations of previous research, enriching the research situation of user behavior on online education, and promoting the sustainable development of online education industrialization.

2. Innovation in research methods. In this study, the PLS-SEM method was used to construct and test the model of factors that impose impacts on users' PI on OEP. Then users are classified into two groups based on whether they have experience in purchasing courses on OEP. PLS multi-group analysis (PLS-MGA) was used for comparison analysis to further discuss the relationship and strength between potential variables that have impacts on the PI of users with different purchase experiences in the model, to explore the factors that have impacts on PI users with different purchase experiences and the impact strength of the corresponding factors.

3.The innovation of integrating the research model, which is a theoretical innovation, to some extent since a model of factors that have impacts on users' intention to purchase courses on OEP was constructed. Based on the previous research, PV is studied as a mediator. According to the current advancement of new technologies, such as mobile Internet, the contextualized variables are added to conduct in-depth research, and the variable of "WM" was introduced a new moderator, which enriches the research on the impacts of each dimension on the dimensions on PV.

4. The sample data come from real users, so the research results are more reliable. Because the data acquisition of online education users was difficult in the past, normally students are used as sample groups, whose representativeness and universality are insufficient. The sample data of this study are all first-hand data from genuine users on OEP.

1.7 Chapter summary

The rapid development of the Chinese Internet has created new opportunities for many industries in China. Online education enjoys the rapid development of the Internet with continuously growing market scale but most OEPs are suffering losses, an acute challenge facing this industry. This chapter takes the background as the starting point, puts forward main research questions and describes the research purpose of this research. The research methods and framework used in this study are also elaborated in this chapter. Analyzing the factors that impact the users' intention to purchase courses on B2B2C OEP, this study intends to provide valuable reference and suggestions for enterprise management, product development, marketing and other OEPs. Finally, the chapter sets forth the theoretical and practical value of this research and extracts the key innovation and contribution.

In the next chapter, he conducted an in-depth review of the relevant literature involved in this study, and expounded the importance and urgency of the research questions, laying the theoretical foundation for the later chapters.

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Chapter 2: Literature Review and Theoretical Foundation

2.1 Literature on PI

2.1.1 Literature of PI

Intention is the premise of behavioral activities. Only when individuals have the intention, can they take certain behavioral activities. Therefore, the individual’s intention can be considered as determination of the individual’s behavioral activities. The term “intention” is initially a concept of psychology, which refers to the willingness of consumers to act and a change in the state of mind of the consumer. It is the possibility that the consumer engages in a certain behavior in the case of receiving certain information or stimuli. In consumer behaviorism, the intention to purchase is considered as a decision-making process, meaning that the consumer has the possibility to purchase or attempt to purchase a product or service.

Eagly and Chaiken (1993) considered that intention is a psychological state different from attitude, and it is an individual motivation to implement a certain behavior with consciousness and plan. Since then, some scholars have introduced the concept of “intention” into the discipline of marketing. Fishbein and Ajzen (1975) identified PI as the subjective probability of consumers purchasing a certain product or service, and they believed that the customer’s PI refers to the subjective probability that the customer engages in a particular purchase. Bagozzi and Burnkrant (1979) defined PI as the consumer’s tendency to buy commodity. They believed that the purchase behavior can be predicted by the PI that is a key indicator to understand the buyer’s subjective tendency. Burke, Hatfield, and Kein (1985) proposed that consumers’ attitudes towards a certain product or brand, as well as certain environmental factors, ultimately constitute consumers’ PI that is the subjective tendency of consumers to choose a certain commodity. He also confirmed that the PI can be used as an important indicator to predict consumer buying behavior. Dodds, Monroe, and Grewal (1991) defined consumers’ PI as the probability and likelihood that a consumer will buy a particular product or service. Ajzen and

Driver (1992) defined PI as a determining factor before behavioral performance and a necessary process for doing the next step. Spears and Singh (2004) concluded that PI is the subjective probability that a customer buys a certain good or service after research. When the attitude and impression of consumers reaches the level of satisfaction with a product or service, they will form an intention to purchase.

Chinese scholars have also defined PI in series of wording and phrasing. Han and Tian (2005) believed that PI is the possibility of consumers purchasing certain goods, which coincides with foreign scholars. Feng, Mu, and Fu (2006) considered PI as the basis for consumers' buying behavior. Zhang (2017) proposed that PI determines whether consumers will buy or not. Pang (2018) argued that an individual has a PI before making a purchase decision, and when the individual's PI is stronger, the individual is more likely to implement the purchase behavior. Liu, Hu, and Tang (2019) argued that having PI is a prerequisite for conducting purchasing behavior.

The research of the majority of scholars on the PI is also deepened with the clarity of this concept. Everyone is more willing to use this concept to predict the shopping trends of consumers in the future. Compared with the traditional PI, consumers' online PI is not much different. Most scholars also believe that online PI refers that consumers are likely to purchase a certain product or service in a virtual environment. Although there is no shopping environment of actual offline consumption in the online environment, consumers are also driven by the PI to buy when making shopping behaviors.

2.1.2 Literature of PV and PI

Monroe (1973) pointed out that customers usually compare the perceived benefit and perceived cost (PC) of purchasing products when making purchasing decisions. When the perceived benefit is greater than PC, the customer has a positive PV for the product. Positive PV will increase consumers' willingness to buy. Similarly, when the perceived benefit of the consumer is greater than PC, the customer will have a PI, and higher PV always causes higher PI. Dodds, Monroe, and Grewal (1991) pointed out that PV has a positive impact on PI in empirical research. Assael, Dymond, and Papadaki (1992) pointed out that higher PV for goods or services during the shopping process brings stronger PI. From the perspective of consumer psychology, Zeithaml (1988) conducted a large number of empirical studies to prove that the higher the consumer's perceived benefit to the product or service is, the higher their feeling of value will be, and higher PV of the product or service will increase the consumer's willingness to purchase the product or service. Teas and Agarwal (2000) argued that the subjective PV of consumers determines their willingness to purchase, and that PV is an important factor in consumers' decision-making. Eggert and Ulaga (2002) also pinpointed that consumer satisfaction is a necessary driver for purchase, but PV is the most important driver for consumers to purchase. Tam (2004) showed that consumers' PV is more likely to trigger consumer buying behavior than consumer satisfaction. Wu and Hsing (2006) constructed a model that how perceived sacrifice affects PV and then PI. The conclusions showed that PV has a significant positive impact on consumers' PI.

Song, Wang, and Xu (2006) pointed out that the PV of consumers usually affects their decision whether to purchase or not. The evaluation result of PV determines the willingness to purchase. Wang, Li, and Ye (2007) suggested that consumers' perceptions of purchasing interests and purchasing risks affect consumers' PV and their purchasing decisions. In the study of online consumers' willingness to purchase, Zhong (2013) took the purchase cost, perceived product quality, PR, perceived website service quality as antecedent variables of consumer's PR online, and concluded that consumers' perceived product quality and perceived website service quality have a significant positive impact on their PV and PI, while PC and PR have a significant negative impact on their PV and PI. Ji (2013) also found that perceived benefits, purchase costs, and PR has direct impacts on users' willingness to consume in the context of online shopping. In the study of the factors affecting the willingness of free customers to pay for value-added services, Li, Li, and Shi (2014) used the network externalities, virtual social capital and network viscosity as explanatory variables of customer PV, and concluded that network externalities and virtual social capital can directly affect customers' PV, which indirectly affects customers' intention to pay, while PV has a direct positive impact on customers' intention to pay. In a study of PV and willingness to channel change, Zhao (2015) found that the improvement of PV promotes higher PI and likelihood of purchase behavior of online consumers. Liu and Tang (2015) believed that it is possible to enhance the PV of consumers by strengthening publicity, thereby stimulating online consumers' PI and shopping behavior online. After conducting an empirical research, Wang (2017) found that the greater the PV of the user, the stronger the willingness to purchase the goods or services. Xu, Zhang, and Dong (2018) found that the PV significantly affects college students' intention to purchase through their research on college students' willingness to pay for online courses. Lin and Qu (2019) conducted a study on the relationship between PV and PI, finding that users' PV has a positive impact on their PI.

From the above research, it can be concluded that factors such as PV, perceived benefit, PR, and PC are the key factors affecting PI in the empirical analysis of consumer PI. Then, whether these factors have a significant impact on the intention of purchasing online courses, and how the various potential factors affect each other needs to be verified through empirical analysis in combination with the situation of purchasing courses on online educational platforms.

2.1.3 Literature of online WM and PI

In the field of traditional marketing and consumer buying behavior research, WM is considered to be an important factor affecting marketing and consumer buying behavior (Huang & Zhu, 2003), since it is able to deliver information about the product or service that helps other consumers make purchasing decisions to the audience. With the rapid development of e-commerce, comments and WM on online products also have an important impact on consumers purchasing a certain product. In the online shopping situation, the e-commerce platform collects consumers' relevant evaluations of a certain product or service based on the comment function to help other consumers make judgments at the time of purchase. These evaluations constitute online consumer reviews or electronic WM for specific goods or services, which can have a significant impact on consumer online PI and behavior.

Park, Lee, and Han (2007) believed that the online comment is an important factor affecting consumer decision-making after empirical research. The quality and quantity of online reviews can positively impact consumers' PI. Lee and Youn (2009) argued that positive online reviews have a positive impact on consumers' willingness to recommend and purchase a product, while negative reviews can have a negative impact. Cui, Lui, and Guo (2012) collected users' consumption data and online comment data for electronic products and video games on Amazon.com when studying the impacts of online consumer reviews on new product sales. The analysis found that the number of online reviews at the beginning of the sale has a significant impact on selling new product.

Hennig-Thurau and Walsh (2003) conducted a research on consumers search for online WM and reading motivation on the online consumer opinion platform, finding that consumers read other consumers' comments of related products when they shop online so as to save time in making their decision on which good to buy and help them make better purchasing decisions.

Chinese scholars have also confirmed in relevant research that in the context of online shopping, online WM has a significant impact on consumers' purchasing behavior, and positive online WM of goods or services can positively affect customers' PI (Bi, 2009; Huang & Lao, 2013; Li, 2015; Lu, Huang, & Li, 2017; Xu, Zhang, & Dong, 2018), negative online WM has a negative impact on PI (Bi, 2010; Guo, 2015; Zhang, 2015; Chen, Wu, & Zhang 2017). Wang (2018) found that both Internet WM and users' perceived quality affect the intention of users to pay in the study of the factors affecting the payment on the audio book platform. Wang, Wang, and Yang (2019) found that WM between acquaintances positively moderates the impacts of PV on PI. Wang, Wang, and Yang (2019) deeply explored the source of WM and the reliability of commentator, all of which demonstrated that both have a positive impact on the user's PI.

It can be seen that Internet WM is an important factor affecting consumers' purchasing behavior in the context of online consumption. OEP users may also pay attention to other users' online comments about a course when purchasing the paid courses. When comments of a course show a good reputation and meets the user's learning needs, the user's PI may be higher. Therefore, in the study of factors influencing user's intention in paying for online courses, he believed that the comment WM may be an important factor affecting the users' intention for buying the course, introducing relevant models for analysis.

Based on the above research results, factors such as PV, PR, PC, and online WM (online comments) have been confirmed to impose impacts on users' PI (the willingness to pay) in buying a product or service in the Internet context in many studies. Therefore, in constructing the model of factors influencing users' intention in purchasing courses on OEP, he learns from the previous research and involves factors that have been confirmed to impose impacts on consumers' PI in other consumption scenarios, and he adds some contextual variables that may affect the user's PI in buying paid courses based on the specific situation of online education. In this way, this study can batter verify which factors affect the user's intention to purchase a paid course and how different factors affect each other.

2.1.4 Literature of online PI

Whether in a physical or an online shopping environment, consumers' intention to purchase goods or services is essentially the same, and it refers to the probability or likelihood of purchasing goods or services. Due to a different way of shopping and environment, the activities of online consumers reflect their own characteristics, which is that the virtual channel, Internet, has been taken as the medium to purchase. The consumer's online PI refers to the probability or possibility that the consumer buys certain product or service after being informed of related information provided by the online store when browsing the online store.

Baker, Grewal, and Parasuraman (1994) believed that the "soft environment" of online shopping is the internal psychological reaction of marketing strategies of e-commerce enterprise. When customers shop online, the shopping environment and atmosphere provided by the website exerts a significant impact on the psychology of customers, and its impacts outweigh the impacts of the product itself on the customer to some extent. Dowling and Staelin (1994) argued that although online shopping provides consumers with a convenient and fast way to shop, it still contains more new risks compared with traditional offline shopping, such as: personal privacy leakage, stolen credit card number and password, lack of product quality assurance, lack of satisfactory service, no delivery after payment, etc. These risks seriously restrict consumers' PI. Shelanski and Klein (1995) proposed that transaction costs are an important factor in affecting consumers' PI, whether it is online or offline. Chiles and McMackin (1996) pointed out that in the online shopping environment, transaction costs refer to the sum of time and risk involved in order to complete online transactions, including purchasing equipment, searching information, learning knowledge, currency, and time. The transaction cost of online shopping is lower than traditional offline shopping.

Sharma (2002) studied the factors affecting consumers' online PI, and he found that among these factors, in addition to the product quality and product price that have an impact on consumers' PI, the website's service to consumers also have a significant impact on their PI. The website's services include its information quality, response time, reliability, and product delivery and after-sales maintenance. He believed that high-quality and fast service can not only reduce the time and effort spent on purchasing products, transaction costs, but also relieve consumers' worries. He pointed out that websites should maintain and develop close relationships with customers through good service, creating value for them. Belanger, Hiller, and Smith (2002) pointed out that aesthetically pleasing, reasonably designed and easy-to-use web design helps to stimulate consumers' desire to purchase, otherwise it has a negative impact on consumers' PI.

Pavlou (2003) argued that compared with the traditional shopping model, it is fair to say that online shopping brings convenience to consumers, so that consumers can get the goods and services they need at a lower price and enjoy the fun. However, it also causes certain risks to consumers, such as: difficulty in guaranteeing product quality, poor after-sales service quality, personal privacy leakage, unavailable is easy to be leaked, non-delivery after payment, and stolen credit card information etc. All the above-mentioned factors exert negative impacts on consumers' PI and hinder the development of online shopping at the same time. Based on previous studies, Lim (2003) summarized the PR of online shopping for consumers into seven categories (quality risk, economic risk, personal risk, social risk, psychological risk, health risk, time risk), and researched the root causes of these risks, which can be summarized as the following four aspects: products, network technology, vendors and consumers. Lim (2003) believed that the risks caused by insufficient technology are the main reason that hinder consumers' online shopping. Lim (2003) believed that the risks caused by insufficient technology are the main reason that hinders consumers' online shopping. Lim (2003) surveyed 1,000 Internet users through requiring each of them for their opinions on each of the following questions and found that 88% of the respondents believe that losses caused by technical issues are relatively more serious for consumers; 82% of respondents believe that losses caused by sellers are more serious for consumers; 78% of the respondents believe that the losses caused by product quality are more serious for consumers; and 92% of the respondents believe that the losses caused by consumers' own are more serious. Liu and Wei (2003) argued that when online consumers choose different categories of goods, the degree of their PI is also different.

Gupta, Su, and Walter (2004) classified consumers into risk-neutral and risk-averse types based on attitudes toward risk, and constructed a purchase decision model including factors such as commodity prices, search costs, time required for purchase, and PR. The quantitative methodology was also used to analyze the different characteristics of decision-making in the context of online shopping and offline shopping for these two types of consumers. The results of the study showed that risk-neutral consumers tend to shop online, while risk-averse consumers tend to shop offline. Among the factors affecting consumers' online shopping, the variety of goods and the time required for purchase are important factors affecting their PI, while the price of goods is not the main factor determining the purchase. Consumers are more willing to visit a retail website with great varieties and easy-to-order operation. Gefen and Straub (2004) believed that trust is generated in the long-term and frequent communication between the two parties. Consumers in the context of online shopping cannot communicate with seller face to face, so it is difficult to establish a trust relationship with the shopping site in the context. Teo and Yu (2004) argued that trust is built gradually through frequent contacts and exchanges between people or organizations, but in e-commerce shopping environment, there exist difficulties in establishing trust between the buyer and the seller because the consumer cannot have face-to-face contact with people. Dailey (2004) proposed that that under the conditions of e-commerce, consumers buy goods online based on their recognition of the design of online stores, so the quality of the interface design of the virtual store directly affects customers' PI. If the interface design of the virtual store conforms to the customer's aesthetic psychology and facilitates the customer to search for information, it helps to create trust between the customer and the company, thus enhancing customer's PI. Dailey (2004) also proposed that e-commerce enterprises should optimize the design of web interface in the four aspects: structure, content, illustration and interaction, so as to convey the information that the enterprise enjoys integrity when operating business to viewers. In this regard, the trust between the viewer and the enterprise can be enhanced, and the viewer can be converted into the customer of the enterprise.

Liu, Huang, and Liu (2004) constructed a model that how service quality affect consumers' online PI. The criteria used to judge the quality of the website include the rationality of web design, interaction and communication, convenience to place an order and delivery speed. Through questionnaire survey and multivariate regression, impacts from these four aspects on the online consumers' PI were studied, and the empirical results show that the rationality of web design and delivery speed affect the consumers' online PI significantly and positively. Wang and Emurian (2005) believed that the quality of service exerts a greater impact on consumers' PI in the process of purchasing goods online comparing with traditional shopping. The service includes not only online services, such as: whether the product information provided online is comprehensive and detailed, whether the questions raised by customers can be answered in time, whether the interface design of the web page is reasonable, etc., but also includes product distribution and after-sales service, and all of these factors have a significant impact on consumers. Zhou (2005) conducted an empirical study on the factors affecting consumers' trust on website, and proposed the following hypotheses: (1) the more familiar consumers are to the website, the more likely they trust it; (2) the higher the security of the website is, the easier it is for consumers to form trust with the website; (3) the quality of website information contributes to the cultivation of website brand trust; (4) the shopping experience helps the establishment of website trust; (5) the establishment of WM trust in website brand and Development is crucial. He used the online bookstore *Dangdang* as the website to research on consumers' trust. Through the path analysis of the hypothesis model, the results showed that the trust degree of B2C e-commerce website is affected by the abovementioned factors, and the website can effectively establish and maintain the trust between consumers and websites by taking corresponding measures.

Xue (2005) summarized the cost factors in online transactions into the following categories: search cost, learning cost, time cost, currency cost, asset-specific cost, risk cost, and proposed that transaction cost factors influencing online transactions in China include: computer and network equipment costs, website design convenience and interface friendliness, network information, time factor, distribution and after-sales service, transaction uncertainty. He believed that in the growth of e-commerce in China, it is necessary to fully consider the transaction cost factors affecting consumers' online purchases and design an e-commerce model that conforms to China's national conditions, thereby reducing transaction costs and increasing consumers' online PI. Liu (2017) argued that the degree of willingness to make purchases via the Internet varies with the purchase of different goods. He divided goods into two categories: tangible goods and intangible goods. Through research, it is found that consumers purchase both tangible and intangible goods online, and the three factors of perceived effectiveness, perceived convenience and PR exert impacts on consumers' online PI. Therefore, he constructed a hypothesis model about how online PI is affected and conducted empirical research accordingly. The empirical results show that PR has the greatest impacts on consumers' online PI. Zhong and Zhang (2013) constructed an empirical model of how consumers' PV affect their online PI and proposed that consumers' PV can be considered in three dimensions: functional value, emotional value and social value. Wu, Chang, and Pan (2014) considered that the online PV consists of three dimensions: online result value, online emotion value, online procedural value that impose positive impacts on online PI. Based on the theory of PV, Sun and Sun (2017) explored the impacts on users' intention when buying fresh products online, and found that PC, entertainment and functionality significantly affect users' online PI, which validates the mediating role of PV. Sun (2018) found that the gender of the user has no significant difference in their online PI, but the online shopping period and online shopping frequency have great differences in the user's PI. Exploring the relationship between PR and online impulse purchase, Cui (2019) divided causes of PR into products, online platforms, online services, and users' own environments, and found that PR affects users; PI significantly. Based on the technology acceptance model (TAM), Li and Wang (2019) studied the user's online PI in the social media environment and proposed that trust is one of the most important factors affecting online PI.

In summary, the definitions and conceptual analysis of each researcher about users' PI are different according to various research objects. The operational definition of PI in this study is in the shopping environment on Chinese B2B2C OEP, the probability of being willing to close a deal after perceiving the price and service of the online course.

2.2 Literature of CPV

2.2.1 Literature of CPV

Drucker (1954) pointed out that consumers buy and consume not only the product, or in a more accurate way, it is not the product and the service that is purchased or consumed, but the value that is conveyed to consumers. In other words, the real needs of customers are the key to determining the maximum customer value, rather than the product or service that the company now offers to customers. It is precisely because customers are the rarest resources of an enterprise, therefore any decision made by the company should be based on obtaining this resource. Fan and Luo (2003) believed that customer value is the value that customers care about in their heart, also known as customer PV, which means that customers consider what they want from their own point of view, and they believe that they can obtain the value via purchasing and using the product. Slywotzky (1996) also pointed out that creating and providing good customer value to customers increases the overall value of the company. Peter and Tarpey (1975) argued that two perceptions exist when purchasing products: characteristics they would like to obtain known as positive value whilecharacteristics they would not like to obtain known as negative value. The margin between these two is the net perceived reward. Positive value is perceived rewards, while negative value is PR. Integrating the research results of various scholars, Zeithaml (1988) summarized the four views about consumers' own PV through conducting interviews, and defined customer's PV as the overall evaluation of the product's utility for the customer, that is, the difference between the customer's perceived benefit and the perceived pay based from the perspective of consumer psychological behavior. According to Zeithaml (1988), when companies design, create, and provide value for consumers, they should start being consumer-oriented and use customer perceived value (CPV) as a determining factor. CPV is divided into four meanings: (1) value is a low price. Some consumers equate value with low prices. As long as they are discounted or ultra-low-priced products, they have high value, indicating that the currency they pay in their value perception is the most important. (2) Value is what you want to get from the product. Unlike the money paid for, some consumers see the benefits they receive from services or products as the most important value factor. This is the same as the definition of utility in economics and is a subjective measure of satisfaction with consumer products. (3) Value is the quality of the price paid. Some consumers conceptualize value as a trade-off between "doing money" and "quality". It is valuable to get quality products at the lowest price. (4) Value is all that you can get with all your efforts. Some consumers consider the factors they pay (time, money, effort) and the benefits they receive. Zeithaml (1988) summarized the consumer's expression of these four values into an all-round definition: CPV is the overall evaluation of service utility that consumers perceive the trade-off between the perceived benefits and cost of acquiring a product or service. This concept contains two layers of meaning: first, value is personalized, different from person to person. Different consumers have different PV for a same product or service; second, value represents a trade-off between utility (revenue) and cost (price), and consumers make purchase decisions based on the value they feel that is not affected just by a single factor.

Sheth, Newman, and Gross (1992) analyzed the composition of PV and concluded that products provide customers with five values, namely functional value, social value, emotional value, epistemic value and situational value. Anderson, Jain, and Chintagunta (1992) and others believed that value is the customer perceived utility comparing the price, which can be reflected in economic, technical, service and social benefits. Gale and Wood (1994) refined this concept as customer value is the market perceived quality comparing to the price of the product. From the perspective of corporate strategy, Butz and Goodstein (1996) analyzed CPV and concluded that when customers believe in a product or service provided by a company or enterprise, this belief enables company to bring more net value to the consumer comparing with its competitors, in which context the benefit is greater than the cost. By developing this differentiation from competitors, CPV is formed. Gardial, Clemons, and Woodruff (1994) also pointed out the value that consumers feel when they buy goods is different from the value that consumers feel when they use the goods. When consumers buy and use a certain product, they measure the value of the product according to the different feelings formed in each stage. Woodruff (1997) pointed out that CPV is the customer's preference and evaluation of product attributes, results after using it, etc., and these attributes and results can help customers achieve their intended goals when using products. Grewal, Monroe, and Krishnan (1998) mentioned that whether consumers buy or not depends on the comparison of the benefits he receives from the products and the price he pays for the product, which is the CPV of a product is derived from the benefits of the product and the cost of obtaining the product. When the perceived benefit is higher than PC, CPV is greater. The magnitude of PV depends on the relative relationship between perceived benefits and the cost that needs to be paid. From the perspective of customer relationship management system, Keeney (1999) pointed out that the total net value of the benefits and costs paid by consumers through the customer relationship management system is CPV. Parasuraman and Grewal (2000) argued that CPV is to weigh customer perceived profit and PC, therefore it is a dynamic concept. It includes four values: firstly, acquisition value, which refers to benefits obtained after paying a certain currency; secondly, transaction value, which refers to the joy obtained by the customer from the transaction process; thirdly, use value, which refers to the utility obtained due to the use of the product or service; fourthly, redemption value, which refers to the residual value obtained after the product is trade-in or the service is terminated.

Sweeney and Soutar (2001) proposed four dimensions of CPV through empirical research: firstly, emotional value which refers to the utility obtained by customers from the sensation and emotion of consuming this product; secondly, social value which refers to utility brought to the society due to the improvement of society self-concept concept; thirdly, quality value which refers to the utility obtained by the customer from the comparison between the perceived quality of the product and the expected performance; fourthly, price value which refers to the utility of the short-term and long-term PC of the customer. Sanchez, Callarisa, and Rodriguez (2006) perfected the definition of CPV from the perspective of travel culture, pointing out that CPV is a series of dynamic variables of consumers at the time of purchase, use and after use. The subjective measurement of CPV also varies over time and culture.

The research on CPV in Chinese academic sector has begun to increase substantially, and these researches link CPV with PI, purchase behavior, customer loyalty and many other elements. Li and An (2008) explored the interrelationship between CPV and perceived quality, brand image and customer experience through literature reviews. Based on CPV, Wang and Xue (2010) carried out an empirical research of a bicycle rider association in Shanghai, researching on the social capital dimension, characteristics and impacts of the brand community, and revealing the mechanism by which the brand community exerts impacts on brand loyalty through the measurement of CPV. Liao and Lin (2009) explored the PV of luxury goods by taking luxury goods as the object of his empirical research. Jiang and Yuan (2009) innovatively introduced consumer personality factors into the measurement of CPV and perfected the research system of CPV theory from the perspective of driving factors. The starting point of his research is that the difference in individual psychology has a significant impact on their PV. Five dimensions of personality were included in this research, which are of openness, extroversion, pleasantness, rigorousness and neuroticism. The impacts of these five dimensions on CPV and the five customer perception models were evaluated comprehensively to study how to improve CPV. Hao (2011) studied the relationship and interaction between corporate innovation behaviors and its brand image, brand management capabilities, CPV, and customer buying behavior, and used an integrated research framework to explore how corporate innovation behaviors, brand image, brand management capabilities, CPV affect consumers' purchasing behavior. Based on the theory of PV, Zhong (2005) found that perceived product quality and perceived website service quality have a significant positive impact on PV and PI of online consumers, while PR imposes a negative impact on PV and PI; purchase cost has a positive impact on CPV but has no significant impacts on PI; PV (functional value, emotional value and social value) has a significant and positive impact on PI; online WM moderates the impacts of PV on PI. Zhao (2013) found that CPV is composed of the overall customer benefits and the overall customer costs in his study. The overall customer benefit is the total amount of money consisting of a set of economic, functional, and psychological benefits expected from its particular supply of the product; total customer cost refers to the estimated total expenditure of assessment, acquisition, use, and abandonment of its particular supply of the product. From the perspective of PV, Chen, Wu, and Zhang (2017) studied the user's intention to purchase genetically modified food through the questionnaire survey, and they researched on the impacts of social value, functional value, economic value and emotional value on the user's PI. It is found that WM plays a role in regulating the four dimensions of PV, and PV also positively affects the user’s PI. It is also concluded that negative WM negatively affects the user’s PI. Fang, Lu, and Liu (2018) found that perceived usefulness (PU) and perceived trust positively affect PV, thus affecting the consumers’ intention to pay in virtual community. Chen, Gu, and Hu (2019) integrated two theories, PV and PR, and further broke down PV and PR to explore how the intention to purchase new energy vehicles is affected. It is found that both PV and PR have a significant impact on the user’s PI. PR has a negative impact on PI while PV has a negative impact on PI.

Related literature illustrates that CPV is not only the premise of their PI and behavior, but also the most important indicator of marketing activities. The research on CPV is mostly carried out from the following three perspectives: Firstly, taking CPV as the core variable, through empirical research or summarizing previous literature to explore the relationship between CPV and enterprise-related variables in order to develop and improve the corporate strategic framework centered on CPV. Secondly, CPV is used as a mediator variable to modify the existing classic models. Thirdly, combining CPV and Chinese practice so that the core concept, CPV in marketing, can be applied to various industries, and guide the development strategy of the enterprise, and finally providing strategies for business operation through the introduction of concepts. Helping companies to gain a dominant position in the fierce competition.

2.2.2 Literature of online CPV

Keeney (1999) argued that PV of online customers should combine the underlying goals and the means objectives. The basic goal is that the shopping website should ensure product quality to minimize the cost of online customer purchases, provide convenience to consumers, protect their privacy, and make consumers feel entertaining during the shopping process. Meanwhile shopping websites that cannot take fraudulent behavior, ensure system security, provide comprehensive information and make it easier for consumers to compare goods, often update the variety of products to meet consumers’ motivations for new purchases, minimize online trading risks, etc. Bourdeau, Chebat, and Couturier (2002) conducted a comparative study of website visitors and email users in college students, from which it showed that the network provides five values to college students, including utilitarian value, social value, and hedonic value, purchasing value and learning value. Bourdeau, Chebat, and Couturier (2002) concluded that most website visitors are looking for a learning experience, enjoying the fun that the network brings to them and thinking that the network brings them new knowledge that does not make them feel painful. They are happy to learn this new knowledge and think that browsing websites can help them to buy the goods they need online. E-mail users pay more attention to social values. They can establish good interpersonal relationships with others through online channels. They use e-mail not to learn as website visitors, but to focus on the communication function of e-mail. Chen and Dubinsky (2003) suggested key factors influencing CPV in the B2C e-commerce environment by establishing a theoretical framework, including perceived product quality, PR, product price and experience value. Perceived product quality includes sub-factors such as shopping website credibility, product price, and experience; PR includes sub-factors such as shopping website credibility, product price, and perceived product quality; experience value includes sub-factors such as website information, consumer service, and ease of use. Mathwick, Malhotra, and Rigdon (2001) conducted an in-depth study on the experience value of online shopping behaviors through the experiential value scale.

In the research on PV of online customers, Zhong (2005) constructed a model of the generation process of online CPV, and argued that online customer perceived profit and loss, characteristics of online customers, and PR impose significant impacts on their PV. According to the research results, Zhong (2005) summarized some suggestions for improving PV of online customers, such as improving product quality, reducing transaction costs, and reducing PR of online customers. Based on the model constructed by Zhong (2005), Xu, Liang, and Xia (2006) added the purchase situation factor to the model and believed that the purchase situation can also exert certain impacts on the PV of online customers. They also conducted an in-depth theoretical research on perceived profit and loss and PR, so as to construct a perceptual value model of online customers. Sun and Si (2007) studied the PV of online customers and constructed a theoretical model for the PV formation of online customers. Through empirical research, it is considered that PV of online customers includes two aspects, satisfaction and sense of trust. The PV of satisfaction is reflected in convenience, commodity price, personalized experience, online customer expertise and service remedy. The PV of trust is reflected in the security of the shopping website, the protection of the privacy of online customers, and the expertise of shopping websites. Zhang (2007) thought that there are many factors affecting PV of online customers. For example, the personal factors of online customers, including their physical and psychological factors, economic status and lifestyle. All these factors have an impact on their PV. Environmental factors also have an impact on PV of online customers, including social environment, natural environment, shopping environment, family, related groups, and their roles and status. Zhang (2007) also thought that social and cultural factors have a certain impact on the PV of online customers, including cultural and subculture, consumer prevalence and social class. Therefore, these factors should be emphasized in research. Through empirical research, Zhong (2013) found that PV (functional value, emotional value and social value) has a positive impact on the PI of online customers, and their PI is not depending solely on the price. At the same time, more attention should be paid to the accumulation of online WM. Liu (2017) found that the exclusive price on platform has the greatest impacts by studying the factors affecting the PI of online customers, followed by entertainment, self-efficacy, convenience and ease of use. Wang (2017) introduced online WM, PV, PU, and PEU into his empirical study to research on the intention of users to purchase agricultural products online. The results showed that PV moderates the impacts of WM on PI, and PV significantly and positively affects PI. Ye and Wang (2018) conducted a research on factors influencing users' intention for content payment on audio-reading platforms. The results showed that personal awareness of payment, PV and perceived price directly affect PI, and perceived quality and online WM indirectly affect PI. Gao (2019) used perceptual value as a mediator to study factors influencing users' intention to purchase fresh products online, and perceived service quality as a moderating variable of the impacts of perceived product quality on PV. The results also demonstrated that PV has positive impacts on PI and mediates the impacts of service quality on PI.

2.2.3 Literature of PR and CPV

Bauer (1960) first proposed the concept of PR, which often refers to the subjective judgment of the characteristics and the severity of the risk, that is, the uncertainty of the decision-making result and the seriousness of making wrong decisions. For example, when an OEP user purchases a course, even if he has a comprehensive understanding of its content and related information, whether he can successfully complete the course after the purchase, whether the course can be as useful as his initial expectation, and whether service provided by the platform can meet his needs still remain uncertain. However, when making incorrect purchase decisions, users may suffer from serious consequences such as delays in learning plans, wasted time and money.

In different situations, researchers have conducted in-depth research on PR and continuously enriched its content. Jacoby and Kaplan (1972) divided PR into financial risk, performance risk, social risk, physical and psychological risk in the study. Peter and Tarpey (1975) considered time risk as an important factor in related research. Theses six factors of PR were further verified by Stone and Grønhaug (1993) via his empirical research as important components of PR.

The impacts of PR on consumers PI has also been verified in previous studies. For example, Wood and Scheer (1996) thought that consumers PI is a function of perceived benefit, PC and PR when consumers evaluate transactions. This view was also confirmed by Wang (2007) in the related research on the factors affecting the PI of online consumers. Ji (2013) researched on the users' PI in the context of online consumption, and found that perceived benefit, PC and PR are factors directly affecting users' PI, and PR has a negative impact on users' PI. Zhong (2013) took perceived product quality, perceived website service, purchase cost and PR as antecedent variables of PV of online consumers, and found that these four factors have an impact on consumer PV and PI. Wang (2013) researched on mobile applications in his empirical analysis of the factors affecting the intention of users to buy APPs, who found that users PR has a significant and negative impact on their PI. In order to explore factors influencing users' intention to interact in the new media environment of automobiles, Wang, Li, and Wang (2017) constructed a structural equation model based on the theory of PV, and concluded that information usefulness, PV, and PEU impose positive impacts on user interaction intention while PR negatively affects user interaction intention. Zhao, Chen, and Du (2018) constructed a structural equation model based on PV and PR theory when researching users' intention to purchase smart real estate. Through empirical analysis, it was found that PR negatively affects PV and perceived quality, while PR positively affects the user's PI. Her research also indicated that PR indirectly affects PI through PV. Based on the perspectives of PR and PC, Liu, Hu, and Tang (2019) used questionnaire survey to collect data, and structural equation model for data analysis. They concluded that in the online environment, both PC and PR affect users' PI, and ultimately affect users' offline purchase behavior. Chen, Gu, and Hu (2019) introduced PR and PV into the research to jointly study users' intention to purchase new energy vehicles, and divided PR into event risk, financial risk, functional risk and physical risk. In the end, it is found that PR negatively affects users' PI, and financial risk is one of the main factors.

2.2.4 Literature of PC and CPV

Perceived transaction costs originated in the field of economics, emphasizing that the transaction subject is rational, and the trader makes decides on transactions in the principle of maximization of interests. Online transaction is full of uncertainty and complexity. Klemperer (1987) studied the banking industry and found that PC includes transaction cost, learning cost, and contractual cost. Zeithaml (1988) proposed perceived sacrifice contains PC in the study of PV, and PC is the cost perceived by the user when using a product. Samuelson and Zeckhauser (1988) believed that PC include economic risk costs, evaluation costs, set up costs, and benefit loss costs.

Dick and Basu (1994) divided PC into time cost, money cost, and cognitive cost perceived by consumers in the payment process. The time cost refers to the amount of time the consumer perceives to spend on the payment. The monetary cost refers to the amount of money the consumer needs to pay. The cognitive cost refers to the cognitive resources that the consumer perceives to pay. The cognitive cost is mainly due to the unskilled mobile payment operation (new technology acceptance) or the risk in the payment process. PC mainly includes property cost, time cost and learning cost. Property cost refers to the money paid for the purchase of the product and its supporting products or services. The time cost refers to the time wasted when using the product, and learning cost refers to effort devoted to learn to use the product.

In this research, when studying the intentions to purchase paid courses on B2B2BC OEP, he based on the results from previous researches on PV and also added theories of PC. Jones, Mothersbaugh, and Beatty (2002) pointed out that PC includes opportunity costs, risk costs, search and evaluation costs before switching, action and cognition costs after switching, set up cost, and sunk costs in the banking industry and hairdressing industry. Lam, Shankar, and Erramilli (2004) conducted research on the tourism agency, suggesting that PC includes money, energy, time, new technology, and uncertainty. Bunduchi (2005) pointed out that e-commerce reduces the time cost in the process of information exchange and decision-making. Rabinovich, Knemeyer, and Mayer (2007) argued that PC depends on the effort spent in the transaction and all transaction-related activities. Wang (2016) found that when studying factors influencing users' intention to pay on WeChat, improved product technology is beneficial to reducing users' PC and increase their PI. When researching on consumers' decision-making styles, Sun and Sun (2017) found that the awareness of price, the awareness of choice confusion and brand loyalty affect users' PI in the mobile Internet environment, and that PC significantly affects users' PI. Wan (2018) concluded that offline PC significantly affects users' online PI in the study of the relationship between users' PI in multiple channels. Lu, Zhang, and Zhang (2019) researched on users' PI from the two aspects, perceived benefit and PC in the study on intention to pay of users who use voice to answer questions in virtual community, and concluded that sunk cost and information acquisition habits affect perceived benefit negatively; switching cost and the individual free concept positively affect PC; perceived benefit positively affects PI; and PC negatively affects PI.

2.2.5 Literature of online WM and CPV

Arndt (1967) coined the terminology WM in the study. He emphasized that WM is an informal, non-commercial way to communicate information about products, brands or services. The real development of WM is mainly due to the research on the impacts of WM on consumer purchasing decisions. Brown and Reingen (1987) believed that WM is feedback generated by consumers after purchasing goods that can positively express consumers' satisfaction with goods or services. File and Prince (1992) pointed out that WM can also negatively express consumers' complaints about goods or services, and they directly impact the expectations and purchase decisions of subsequent consumers.

With the development of the Internet, online WM came into being. At present, there are different forms of online WM, such as virtual WM, online forum review, online WM, and electronic WM. Although the definition of online WM is different, the basic connotation is the same, therefore this thesis uses the wording of online WM. Research conducted by Staus (1997) showed that online WM is a way for consumers to consult, feedback, express their satisfaction or dissatisfaction about products, and this way of existence can even be the on the message board and information release column on the company website. Gelb and Joson (1995) and Chatterjee (2001) pointed out that online WM is the communication of information on goods and services by consumers through the Internet platform and experience discussion on the Internet after a large number of consumers using the goods or services. Dellarocas (2003) thought that online WM is a two-way communication between consumers through the Internet. On the one hand, consumers can share their feelings and experiences through online WM to reflect the quality of products and services related to enterprises; on the other hand, potential consumers can be helped to make better purchasing decisions by reading the online WM provided by previous consumers. If these potential consumers buy the good or service, they can then provide feedback on the products, so online WM exists in many forms. Datta, Chowdhury, and Chakraborty (2005) suggested that this is also a positive or negative process that experienced customers feedback goods and services to less experienced consumers. Bhatnagar and Ghose (2004) and Sun, You, and Wu (2006) proposed that the widespread use of Internet platforms has caused the spread of WM without boundary restrictions, greatly enhancing the speed and scope of WM communication and making WM easier to store.

Online WM and traditional WM have the same connotation. The only difference is that the form of existence and support is different. Traditional WM is spreading and passing from mouth to mouth, and this form of communication is not easy to record. Online WM continues the form of traditional WM communication, while with the help of the Internet, the original mouth-to-mouth mode can be recorded on the Internet, which is more conducive for consumers to review and storage and for the communication of WM. Hennig-Thurau, Malthouse, and Friege (2010) argued that the spread of online WM refers to consumers' evaluation of experiences on specific goods or services on the Internet platform, and potential consumers can browse these platforms on the Internet to obtain relevant knowledge. He (2015) found that online commentary plays a role in moderating the image of the comprehensive B2C online store and the PI, which affects the PV and PI of the user. Chen, Jiao and Li (2017) carried out a research on users' intention to purchase genetically modified foods and found that the factor of WM moderates the impacts of PV to PI. Ye and Wang (2018) found that online WM significantly affects users' PV in the study of users on an audio platform. Wang, Wang, and Wang (2019) divided WM into WM from acquaintances and WM from strangers in the study of the relationship between Internet WM, PV, and PI, and discovered that WM from strangers affects users' PI and PV while WM from acquaintancespositively moderates the affect from PV to PI.

Online WM exists in a variety of ways, such as online shopping mall, blog, microblog, email, instant messaging (such as QQ, Wechat), discussion group, user comments sites (such as dianping, Maoyan) and other cyberspace.

In summary, different communication platforms and different interactions make online WM have four different forms. However regardless of the form of online WM, its essence refers to the dissemination of relevant comments on products or services by consumers through the Internet platform. The development of Internet technology has made WM communication more convenient, and the number of online WM has soared, making online WM one of the hot topics of current research.

2.3 Theoretical foundation for PI

2.3.1 CPV

In the field of marketing and consumer behavior research, scholars generally believe that CPV is an important reference for consumers to make purchasing decisions. Higher value perceived by customers when purchasing goods indicates higher possibility of purchasing actions take place.

Porter (1985) proposed the buyer value theory which refers to the cost of the purchase of products or services minus the cost. He believed that companies can only gain a dominant position in the competition by providing consumers with more than expected value. There are two ways to increase the value of the buyer. One is to increase the consumer's income, and the other is to reduce the cost of the consumer. In addition to the monetary cost, the cost of the consumer includes time cost, opportunity cost, etc., and the shopping conditions are convenient. Whether it is or not is also an important part of consumer costs. Porter elaborates the theory of buyer value from the perspective of enterprises. He believes that in order to obtain competitive advantage, enterprises must pay attention to and take certain measures to improve the buyer's value of consumers.

Zeithhaml (1988), a well-known American marketing guru, studied CPV on a product or service after weighing the benefits of perceived benefits and costs. The overall utility evaluation, that is, the PV of the consumer is the result of the consumer's evaluation of the trade-off between benefit and cost. This view was widely recognized in subsequent research and further developed. For example, Dodds, Monroe, and Grewal (1991) considered PV as "perceived benefit" and "perceived sacrifice" when consumers purchase goods or services. He also defined the boundary of perceived benefit (including product entity characteristics, service characteristics, etc.) and perceived sacrifice (including acquisition costs, transportation, maintenance, and potential failure risks). Kotler (1994) considered CPV as the difference between the value of all products (cognitive monetary value) and the cost (estimated cost) from the perspective of the value of the transfer; In the relevant research, Sirdeshmukh, Singh, and Sabol (2002) proposed that PV refers to the time, money, energy and other costs that the consumer pays when acquiring the product or service. It is worthwhile to purchase the product or service. Many scholars in China also conduct relevant research. PV is generally considered to be based on the overall utility evaluation of income and trade-offs (Bai, 2001; Fan & Luo, 2003). According to the above connotation of PV, it is believed that CPV is not inherent in the product or service, nor is the company's desire or imagination, but determined by the customer's perception (Ji, 2013).

Ravald and Gronroos (1996) proposed the theory of customer value process based on the relationship between customer profit and loss and believed that PV is the overall evaluation of utility by consumers based on the perception of profit and loss. In fact, this view does not consider the relationship between consumers and businesses. Because the customer value is based on the premise that the company and the customer are constantly understanding and interacting with each other, this is a long process. Therefore, customer value is the result of a period of accumulation, which is the process of value generation. Woodruff (1997) pointed out in the study of the change in value perception during the consumer purchase process that the customer would evaluate the value that the product or service brought to itself before deciding to purchase, and then proceed to purchase on this basis. After receiving the goods or services, the customer also makes a final evaluation of the personal experience of the goods or services. This final evaluation is the starting point for the next purchase and decide whether to make another purchase. At different stages of the purchase process, the PV of the customer is different. When the prior value is evaluated as positive, the consumer will purchase and vice versa. Woodruff (1997) built a hierarchy of customer values that explains the value attributes, evaluation results, and final goals. Through this constant process of PV, it is pointed out that CPV alternates between comment and purchase. Kotler (1994) explained the customer value from the perspective of customer transfer value and customer satisfaction and proposed the customer transfer value theory. He believed that the customer transfer value refers to the difference between the total value obtained and the total cost paid. Among them, the total value includes personnel, products, services and image, etc. The total cost includes physical strength, time, currency and so on. At the same time, it is pointed out that before purchasing a product or service, the customer compares the value of the desired product or service with the expected value. If the value of the desired product or service is greater than the expected value, the consumer is satisfied with the product or service and It is possible to make a purchase again, and if the value of the desired product or service is less than the expected value, the consumer will be dissatisfied and give up the purchase.

In addition, domestic and foreign scholars also defined PV from the perspective of PV components. The consumer value model proposed by Sheth, Newman, and Gross (1992) divided CPV into epistemic value, functional value, social value, and emotional value, contingent value. The value component model proposed by Kaufman (1998) divided CPV into reputation value, exchange value and utility value. Sweeney and Soutar (2001) thought that

CPV can be measured in terms of quality, price, emotional and social factors.

As for factors affecting CPV, previous studies have increased the antecedent variables of PV for empirical analysis. Among them, there are direct causes of perceived benefits (e.g., perceived profit) and perceived sacrifices (e.g., perceived loss) as the antecedent variables of PV (Dodds, Monroe, & Grewal, 1991). Some scholars used PR, purchase cost, service quality, and product quality as an antecedent variable that affects CPV (Wood & Scheer, 1996; Zhong, 2013). Sun and Sun (2017) introduced the style of consumer decision-making and the theory of PV to research on consumers' intention in buying fresh products on the internet. Ye and Wang (2018) used the PV perspective to construct a model of users' PI on audio reading platform. Chen, Gu and Hu (2019) conducted a research on the use's intention to pay for knowledge based on the PV theory and ECT.

Therefore, CPV is the user's perception of the product and service's perceived profit and the balance of profit and loss. The overall utility evaluation of the production is generally recognized and confirmed by previous scholars. The author analyzes the effect of PV on the user's willingness to purchase the course. PU was used to measure the user's perceived benefits for the purchase of paid courses; PC was used to measure the user's perception of the price of the paid course, the cost of purchase, etc. As a factor of perceived loss and loss, construct the basic model of the impacts of PV on users' intention to purchase courses.

Although scholars in the past have comprehensively explained the theory of customer value based on different angles, they had a relatively consistent understanding and understanding of the essence of customer value. Scholars believed that consumers' perception of value determines their PI and behavior. When purchasing goods or services in an online store, greater consumer value brings greater likelihood of a willingness to purchase, and vice versa. Therefore, under the guidance of the CPV theory, it is necessary for this study to conduct an in-depth study of the relationship between PV and PI. Finally, based on the PV theory, this study puts forward the impacts model of PV on the intention to purchase the course, as shown in Figure 2-1.

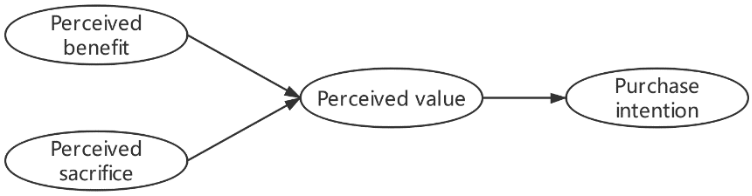

Figure 2-1 Theoretical framework of CPV

2.3.2 PR

The concept of PR originated in the field of social psychology and was later introduced into the field of information technology acceptance and consumer shopping behavior research. It has been verified by many scholars as one of the important factors influencing consumers' PI. PR-related theories hold that consumers have a subjective feeling that cannot be accurately predicted when making a shopping decision. The uncertainty of the outcome of the purchase decision causes consumers to have negative consuming sentiment, which in turn affects their ultimate PI.

Bauer and Cox (1967) defined PR as the uncomfortable consequence of consumer behavior that cannot be accurately predicted by itself. It consists mainly of two sides, namely, uncertainty and adverse consequences. Their study distinguished the subjective perception of risk from the objective existence of risk and took the consumer's subjective perception channel as the starting point to study the impacts of the resulting negative state on consumer behavior. The research laid the foundation for the PR theory and its framework inspired many theories and practices later. The specific application of PR theory is based on the establishment of specific risk dimensions, and the risk dimensions to be adopted in different areas of PR research are different. Many researchers included the consumer perspective as one of their dimensions to research on PR theory (Gao, 2004; Yu, Mao, & Cao, 2011), and they systematically summarized and compared the dimensions selected by domestic and foreign scholars under the general shopping scenario and online shopping scenario, and discussed these dimension in the context of the Internet.

Based on the research conducted by Stone and Grønhaug (1993) and others, this study has drawn the composition of PR proposed by Shim, Eastlick, and Lotz (2000), and this study mainly focuses on the time (time risk) that users spend on choosing to purchase paid courses, money (cost risk) that is whether the cost spent is worthwhile, whether the learning expectation and the purpose can be achieved (performance risk) to measure PR. According to research related to online consumer behavior in the context of Internet, the impacts of PR on consumer PI has also been confirmed in previous studies (McKnight, Choudhury, & Kacmar, 2002; Huang & Zhu, 2003; Park, Lee, & Han, 2007; Huang, 2017). PR has also been introduced to study users' PI for many times (Liu & Tang, 2015; Zhao, Chen, & Du, 2018; Wan, 2018; Chen, Gu, & Hu, 2019; Meng, Jiao, & Liu, 2019).

It can be seen that PR is a key factor affecting consumers' PI. Higher risk perceived by consumer imposes greater negative impacts on their purchasing decisions, therefore reducing their PI. In the context of Internet consumption, users of OEPs also have different levels of decision-making risk when purchasing a course. Based on previous researches, this study introduces PR as a variable negatively influencing users' course PI when constructing the model of factors that impact users' intention to purchase courses, and the study also verifies whether PR is also applicable in the context of Internet consumption scenarios for paid courses through empirical analysis.

2.3.3 TAM

Davis (1986) proposed a TAM which consists of six variables: external variables, PU, PEU, attitude, behavioral intentions, and usage behavior. It is mainly used to explain and predict the acceptance of users' continuous use of information systems.

The model is based on the theory of rational behavior, and two concepts, PEU and PU were proposed. Among them, PEU mainly refers to the user's subjective ease of use of the information system and PU mainly refers to the subjective performance improvement of users using the information system. Davis (1986) also argued that PU and PEU can replace "subjective norms", so the model excludes "subjective norms" and their corresponding influencing factors "normative beliefs" and "compliance motivation".

Davis (1986) found that the usage behavior is mainly affected by the user's behavior intention that is determined by the user's attitude and PU. At the same time, the user's PU and PEU have a direct impact on the user's attitude to some extent. In addition, PU is directly affected by PEU because the user's perception of the usefulness of the system takes time. If the system is not easy to use, it may stop user from continuous use of the system, therefor the user will not be aware of the usefulness of the system. External variables in the model generally refer to system characteristics, user intervention design, and the nature of the setup process.

Venkatesh and Davis' TAM (1996) continued to improve the "attitude" in the original model, and the reconstructed model was more intuitive and clearer, as shown in Figure 2-2.

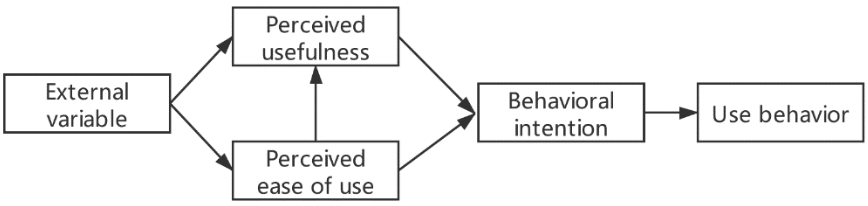

Figure 2-2 Improved TAM according to Venkatesh and Davis (1996)

Zhou (2014) believed that the explanation of the TAM and the validity of the scale are continuously verified in different user groups, different technologies, and different organizational environments, and the model itself is continuously improved. Foreign researchers have launched a large and extensive range of empirical research in the context of different technology applications, such as office automation software, various educational websites, telemedicine, search engines, electronic bulletin systems, e-commerce websites, electronic supermarkets, virtual stores, etc. The research results confirm the explanation and effectiveness of the model to a considerable extent.

According to a large number of literature and content analysis, it is found that the TAM is also used in a large number of empirical studies to explore the user's PI (Li, 2016; Huang, 2017; Ma, 2018; Li & Wang, 2019). Therefore, this study also used the TAM to explore the factors affecting PI of users on OEP.

2.4 Chapter summary

This chapter is the theoretical support for the entire study. This chapter summarizes the research results of domestic and foreign scholars on the factors affecting consumer online shopping, CPV, online WM and online consumers' PI. The focus is the arrangement of relevant research on CPV, including its connotation dimensions, and online consumers' PI. At the same time, it is found that the use of PV theory to study the consumers' intention to purchase online is not systematic enough, because this perspective ignores the role of online WM. This chapter also sorts out the research progress and achievements of online education and PI at home and abroad and provides a theoretical basis for the construction of the theoretical model of factors influencing users' PI on online platform. In this chapter pointed out inadequacies of existing research results and the content of new things that need to be studied, which highlights the importance and urgency of the research questions in this study. Based on the research results of online education, PV, PI, online WM, etc., the characteristics, dimensions and measurement methods involved are summarized. The basic theories adopted in this study have been verified and proved for many times in the field of PI, CPV, and e-commerce. Some mature models with good measurement criteria for users' PI are included here in this chapter, and on this basis, the suitable model is extracted. Therefore, the research content of this part is especially important, which lays a theoretical foundation for this research.

Find the relevant literature and in-depth reading of this research, he combined with the research background and research objectives of this research topic, elaborated the content of CPV theory, PR theory and TAM theory. Finally, he analyzed the role of the three basic theories in this research, preliminary extracted and summarized eight indicator variables including course PI, PV, PR, PC, WM, PU, PEU as the basis of this study, and their rationality was verified and measured in later chapters.

Based on the research of scholars at home and abroad, the research proposes the direction for this study: this study intends to use PV as a mediator to study its impacts on online PI, and use online WM as a moderator to study its role in PV and PI. At the same time, this research also summarizes the inadequacies of various literature and based on which clarifies the main content and direction of this research.

Chapter 3: An Overview of B2B2C OEP Industry

3.1 An overview of online education

Miltiadou (2001) considered online learning to be a rich and dynamic way of learning. It provides attractive learning programs that rely on the Internet and computers and provides lifelong learning opportunities for many people who cannot go to college. Piccoli, Ahmad, and Ives (2001) argued that online learning is an open system that emphasizes the important role of technology, interactivity, and self-control throughout the online learning process. Harasim (1995) pointed out that online learning is a learning method that uses the Internet to provide learning content that breaks the time and place constraints.

He (2005) reviewed the history of the development of educational technology: In the early 1990s, the American education community raised the question of whether “a traditional university with walls will be replaced by a network university without walls in the near future”, which sparked a heated debate for several years. The two sides who agreed that it would be replaced and those who thought it would not be replaced had their own opinions and reasons that they could not reach a unified conclusion. This debate about the way of education in the future has gradually sprawled from the United States to the rest of the world, attracting the participation of many scholars and educators in the United States and the rest of the world. However, the two opposing views failed to reach an agreement. However, after nearly 10 years of online education exploration and experience accumulation, American educators and international education professionals have summarized the profound advantages and disadvantages of online education, reaching some practical basis about whether the traditional brick-and-mortar schools will be replaced in the future. Both sides realize that there is no absolute substitution or non-replacement. Instead, online education and traditional education in brick-and-mortar schools enjoy high complementary, just like that e-books and paper books can coexist and complement each other.

United States Department of Education (USDE, 2014) pointed out that “e-learning” can achieve some of the educational goals on the condition of appropriate pedagogy and curriculum design, but it is not able to replace the teaching effect brought by traditional classrooms; e-learning will not replace the traditional education model, but it will greatly improve and enhance the teaching experience and teaching methodology. USDE defined "e-learning" in a more comprehensive manner, which is at the outset it is education and related services through the Internet; second, it provides learners with a new way of learning and a carrier of learning anytime anywhere; third, the combination use of information plans and various tools can achieve some of the educational goals to help improve the teaching effect, but it cannot replace the traditional brick-and-mortar teaching, nor the traditional school education. These lay the foundation for the new terminology, e-learning, to be popularized and widely accepted in the United States and even the world in the future.

"10 Best Teaching Technology Application Projects in the United States in 2003" was selected in 2003 (Mao, 2003). From the teaching technology application projects selected by this event, it can be seen that many teaching projects use online information technology to develop and implement their online educational behaviors. It also fully shows that the development of information technology and the popularity of the Internet have promoted a great upsurge in producing online educational content and further catalyzed the development of upstream and downstream industries in online education sector.

Moallem (2003) suggested that the use of only online communication tools cannot promote learning, but they can be turned into effective online learning tools through careful design. Carson and Margulies (2004) conducted a survey of online education in MIT and concluded that most users of online education in MIT are from North America, but the internationalization trend is more prominent. Self-learners usually have a bachelor's or master's degree.

In 2008, Canadian professors Stephen Downes and George Simens first proposed the concept of massive open online courses (MOOC). MOOC emphasizes the way of learning from human-machine interaction, making full use of social interaction tools such as Facebook, Wikipedia, blogs and forums to provide online teaching resources, teaching processes and learning discussions. This new teaching model and teaching organization is completely different from traditional teaching in classroom. It has two notable features. First, the group of learners is open. The courses not only allow students on campus to register, but also students outside the school to register. Second, there is no time-space limitation. MOOC breaks through the time and space constraints of traditional ways of teaching, making teaching and learning more flexible, and expanding classroom teaching to accommodate more participants.

Dong (2015) analyzed China's online education business model, finding that the content of online education can be described in the following four aspects. First, online education is supported by the Internet, breaking the time and space restrictions. It allows users to be educated and learn at any time and any place, creating a good learning environment for learning. Second, with the popularity of mobile terminals and technology upgrading, online education is no longer limited to traditional PC computers, but can also be readily accessible through mobile devices such as mobile phones, tablets, and smart TVs. Mobilization, fragmentation, and intelligence have become three characteristics of online education. Third, online education is not just a simple education informationization or educational equipment updating, but it is about changes in the whole process of educational content, educational forms, educational themes, etc. If users have specializations, they can become teachers of the OEP, which also refreshes the traditional definition of teacher. Fourth, thanks to the convenience of Internet communication, OEPs can pool and aggregate individualized learning needs that used to be scattered around the world into the OEP, providing personalized and customized education through the matching of big data. This learning method not only can improve the educational results, but also can enhance education segmentation, thus teaching students according to their different learning abilities and aptitudes. It bids farewell to the traditional standardized teaching content of the past, offering targeted education while further enhancing the learning experience.

Allen and Seaman (2016) defined the traditional face-to-face education, online education, and mixed education, stating that courses with more than 80% content learned online can be classified as online education. IResearch (2018) considered the popularization and application of PC computers and the Internet, as well as the widely adoption of digital multimedia technology in the process of education and training, provide new channels for accessing educational resources, and officially promote the development of online education. Before the birth of online education, education informatization promoted the modernization drive of education. The teaching forms such as slides, projectors, radio, television, audio and video tapes accelerated the process of information transmission, and improved the efficiency of education, laying a solid foundation for the emergence of online education.

ERCICI (2019) divided the development of online education into three stages: the late 20th-2009, 2010-2014, and 2015 to date, are respectively defined as the germination period, the outbreak period and maturity period. It also pointed out that 2013 is year one of the online education era, and the development of new technologies such as artificial intelligence, big data, cloud computing, and augmented reality (AR), has been promoting online education to thorough and impeccable human-computer interaction.

Since the introduction of online education, Chinese scholars have published many theses on online education from various angles. Yu and Lin (2003) analyzed application cases of education informatization in China, pointing out that China has a vague definition of the development of online education, the content of online courses is broad, the construction of learning environment lacks a good design and the form of teaching performance is monotonous and lacks feedback mechanisms for interaction and evaluation. Ding (2004) put forward opinions on accelerating the key discipline construction of distance education and how it can promote the long-term development of online education. He also encouraged to innovate content of subjects and teaching forms to promote the innovation-driven development of online education. Fang and Liu (2006) studied the OEP of Marshall University in the United States, concluding that OEPs should consider five management dimensions: teachers, curriculum development, curriculum evaluation, organizational efficiency and external relationship.

Peng and Zhou (2006) divided online education into two categories according to the infrastructure: Internet-based online education and campus network-based online education, suggesting that the enhancement of the service level of the OEP should guarantee five achievements: developing more high-quality online courses, increasing research of technology platforms, providing better interaction, building an evaluation feedback mechanism, and providing personalized learning services. Gao (2008) proposed a leading online learning model by studying foreign OEPs, and advocated learning through interpersonal interaction on online platforms, thus solving some problems in the independent and self-directed learning mode.

Jiang, Zhang, and Huang (2008) conducted a case study and validated that tutors' active participation and the effective organization have a significant correlation with the completion of homework; the teaching and discussion organized by tutors have a significant correlation with the level of knowledge collaboration in group; and the tutors' emotional support has a significant correlation with the level of knowledge collaboration in group and the building of a good communication atmosphere.

Li and Jiang (2009) used the content analysis method to conduct a statistical analysis on the posting behavior of teachers in the online course, Distance Education Research Method jointly established by the School of Professional and Continuing Education of the University of Hong Kong and the Peking University School of Continuing Medical Education, and they found that sufficient sense of presence in online teaching generates a good way to ensure teaching efficiency. Hu, Han, and Wu (2010) suggested that the curriculum design of online courses should focus on the nature and characteristics of the curriculum through the study of the mathematics and culture courses, online teaching should also create a pleasant learning environment, and the active participation of teachers can boost learners' confidence in learning. Therefore, curriculum design needs to highlight interaction so as to enhance the fun of the course. Zhang (2018) put forward the advantages and disadvantages after conducting research on China's rapidly developing online universities, and believed that the convenience, cost-effectiveness and sharing characteristics of online universities provide new channels for the popularization of educational resources, but because the teaching activities are completely carried out through the network, which may causing insufficient interpersonal skills, collectivism, team collaboration ability, and value education of students, and online education cannot supervise and remind students.

Chen (2010) took online adult higher education as the research focus, carrying out an empirical research on the problems faced by Chinese adult higher education combining with the limitations of online education, such as low time and space restrictions, rich learning resources and flexible learning forms. He recognized the role of online education in China's adult higher education, suggesting that it should continue to increase innovation and reform. Qi (2012) elaborated some common misunderstandings of online education from the aspects of users suitable for online learning, number of students in an online courses, online teaching costs, education quality, learning environment, suitable course content, learning consciousness, and computer literacy, then he objectively argued the advantages and disadvantages of online education to truly achieve the teaching goals of online education. Han (2012) made a new exposition of the new online education model in the web 2.0 era, emphasizing that the online learning environment built by the web2.0 OEP can realize socialized and humanity-orientation learning, ultimately improving the effectiveness and experience of online learning.

Wang and Xu (2012) believed that adult education, online education and self-taught higher education examinations are three important components of Chinese adult education. In 2010, the number of students enrolled in adult education in China reached 5.36 million, the number of students enrolled in online education was 4.53 million, and the number of students enrolled in course for self-taught higher education examinations was 595,000. The three models of adult education show a complementary and integrated development trend. They suggested that the development of adult higher education should be supported by changing educational concepts, optimizing the curriculum system, improving methodology, and strengthening the building of teaching staff. China Industry Research Institute (2019) pointed out that online education is a way of using knowledge technology and Internet technology for knowledge dissemination and course learning. CINIC (2019) found that the rapid development of live broadcast, cloud computing, big data, cloud storage and other technologies has created a good learning atmosphere for online classrooms, and one-on-one teaching method that can meet the individualized teaching needs and break the time and space constraints to provide a great convenience for teaching and learning. Su (2019) believed that online education brings together more high-quality resources, offers transparent curriculum content, breaks through time and space restrictions, saves costs, and meets the needs of using fragmented time to learn, so it has been developed rapidly.

Chinese scholars began to conduct research on MOOCs since 2012. Li (2013) pointed out that a MOOC provides an innovative source of ideas for traditional teaching methods. There are also many differences between MOOC and previous online open classes. MOOC pays more attention to who participates, how participants are evaluated, and what problems and ideas participants have. MOOC has an important inspiration for changing the traditional teaching model in classroom that has lasted for hundreds of years. A MOOC also brings more possibility and space for innovation in education. Yuan, Powell, and Ma (2014) based on the theory of destructive innovation and the theory of sustaining innovation, conducted a research which found that MOOCs provide a new exploration channel for colleges and universities to seek funding, ensure quality and recognize students' credit, fully recognizing the contribution of MOOC to higher education that includes promoting higher education institutions to ponder over new teaching methods, business models and learning flexibility. Li (2013) proposed that the rise of MOOC challenges the traditional market where universities sale academic qualifications in a package, using the enterprise boundary theory and information economics of new institutional economics, and found that MOOC helps to improve the quality of Chinese higher education courses and eliminate inferior quality. The MOOC not only brings excellent courses to China, but also brings opportunities for China to offer excellent courses to the world in the MOOC format.

Gu, Hu, and Cai (2013) proposed the differences between MOOCs and traditional online education in terms of technology platforms, teaching methods, knowledge, copyright of resources, learning and technology through analyzing the development history of MOOCs and their international development background, and comparing them with the development environment and possibilities in China. Wang (2013) found that many well-known institutions of higher learning in the world began to embrace MOOCs and believed that they should have an open view of MOOCs. However, whether MOOCs will be integrated with higher education in the future requires further development of MOOCs technology. If MOOC technology in the future can help users analyze what they want to learn and make learning fun and efficient, perhaps the future MOOC will replace the current higher education system as the main way of learning. Jiao and Jia (2011) researched on the movement of open educational resources worldwide, which sheds lights for the construction and application of higher education resources in China, and its feasible ways contain mechanism innovation, resource creation and sharing, and application of quality resources.

Through literature and research, it was found that there are multiple versions and definitions of online education. China Business Research Institute (2019) pointed out that there are some slight differences among online education, online learning, online training, online education, e-learning, etc. After nearly 30-year development of new technologies and new models, it also verifies that there is no substantial difference between the connotation and essence of theses above-mentioned terminologies. Therefore, this study defines online education as a learning behavior based on Internet knowledge acquisition. It is an educational and learning activity in which the students and teachers use the Internet as the medium of communication. Thanks to online courseware, online video, web audio, online Q&A and other online tools, students can learn at any time and any place. Different from traditional education in school, it breaks the time and space constraints. The advantages of online education are: exceeding the limitations of time and space, and human and material resources, maximizing the use of resources, conducting learning behaviors at any time and any place, interaction with teachers and students, learning independence, mastering learning progress, obtaining immediate feedback, innovating the form of teaching, the adoption of new educational tools, and automatic online teaching management.

3.2 Business model of online education

3.2.1 OEP Classification and business model

China Business Research Institute (2019) classified Internet online education into ten categories: preschool education, maternal and child, adults, foreign language, vocational skills, children’s English, hobbies, international students, college students, primary and secondary school students and vocational examinations. Huang (2017) pointed out that the demand for vocational skills training, English training and tutoring in primary and secondary schools is relatively high in the OEI in China, while civil servant examinations, postgraduate examinations and foreign language are also hot areas of online education. However, the content of online education is not limited to these topics. Each OEP has launched a variety of paid online learning services, covering a wide range.

IResearch (2018) classified OEPs into comprehensive platform, vertical platform and

MOOC platform. The specific classification refers to the following table:

In the current market-oriented OEI, online education services cover a wide range of forms, and there are many types of companies involved in the OEI, including traditional training companies, emerging training companies and Internet business giants. The OEI has two main ways to charge consumers. One is to pay for courses and studying materials, and this way is mainly used by suppliers who provide high-quality digital and original course content. The other way is used by online education institutions that charge users by providing them with relevant examination services, online testing services, educational consulting services, and related professional services.

IResearch (2018) believed that the current online education business model mainly relies on course sale to make profits where the platform acts as an intermediary. One end is connected to teachers who provide online education resources, and the other end connects students who have educational needs. Currently the main profit model is that students pay course fees to online teachers through the platform, and OEPs charge commissions for course fees as a source of income. Various profit models can be explored in the future. In the process of teaching, the platform can operate in a similar way to live broadcasts. Students can reward teachers online, and the platform can also extract commissions from rewards. After teachers and suppliers entering the platform, they still need to carry out publicity and promotion. The enrollment, teaching, management and service tools provided by the platform can also improve the efficiency of teaching work. As a result, future platforms can charge some additional fees on inventory and web tool resources. There are many ways to increase income of OEPs in the future, but the current source of income for them is still dominated by the sales of online courses.

3.2.2 Comparison of B2B2C OEPs, B2C online school， and knowledge-based pay

Jiguang Big Data (2017) summarized the mainstream knowledge paid APP after research: knowledge-based payment has certain universality and systemicity in the fields of publishing, education and training. The knowledge paid by the public mainly refers to the soft knowledge that is the knowledge products that the consumers consider to be valuable and non-standardized by the users themselves, such as the practice summary and experiences of the knowledge cognizers.

IResearch (2018) conducted a comparison of B2B2C OEP, B2C online school, knowledge-based payment platform and found that B2B2C OEP and B2C online school both consider education realization as their ultimate goal, B2B2C OEP is an open carrier aggregating curriculum in multiple fields, B2C online school is a network carrier that focuses on self-operation education. The B2B2C OEP and the B2C online school platform are both aimed at carrying out skills training and online education, moving the traditional teaching scene to the online. The difference between these two is that as an open carrier platform, the B2B2C OEP is responsible for the function of the educational carrier, via a role in the aggregation and distribution of various vertical courses. The B2C online school is the network carrier for the self-management of the education subject. Generally, its main course products are relatively vertical education fields, such as language training, vocational training, and skills training.

The B2B2C OEP and knowledge-based pay platform are both open content and resource aggregated platforms. Pang (2018) pointed out that the B2B2C OEP mainly focuses on the model of education service based on platform, while the knowledge-based pay platform focuses on sharing and disseminating fragmented and light knowledge. It was believed that the B2B2C OEP and the knowledge-based pay platform are all open platforms for the aggregation of third-party knowledge and content. As an intermediary role of the education carrier, they link the content provider and the content receiver at two ends. Both can provide delivery channels, information system function, and other supporting service in the process of education (knowledge) sharing and dissemination, and in the meanwhile of implementation, knowledge can be sold off. However, there are some differences between the two. The B2B2C OEP focuses on providing structured and systematic professional education services as the main content, often in a business model combining multiple education types with courses as its core products. Paid platforms are often based on services sharing and delivering fragmented light knowledge. The sharing and dissemination methods are relatively simple and convenient. Generally, text, images, audio, video, and other light multimedia transmission methods are used as the carrier to achieve the goal of knowledge transmission.

3.2.3 An introduction of B2B2C OEPs

Pang (2018) defined the OEP as an Internet third-party education platform that links the educational resources at both the supply and demand sides, provides online technology, information system functions and services for all aspects in the teaching process, and accomplishes the realization of educational resources.

IResearch (2018) defined the B2B2C OEP as a third-party educational services platform that provides supporting service for online education and the profit realization of educational resources and contents. From a macro perspective, the B2B2C OEP refers to the Internet third-party education platform that aims to achieve quality education and links both educational content providers and demand side. It is normal that as a service provider, the platform does not produce and provide resources of educational curriculum. The bulk of its responsibility is to assume the role of the carrier platform for education on the Internet, providing multi-faceted support and Internet technology services needed in all aspects of the teaching process. The B2B2C OEP helps the education content providers to realize the productization, commercialization and branding of the curriculum to achieve the goal of realizing the profit of the educational content while providing basic conditions to implement education.

TRI (2019) argued that the OEP of B2B2C business model refers to online education training institutions and individuals provide services of a large number of educational curriculum for individual users through entering the OEP. The content of B2B2C OEP is more comprehensive, and relying on the platform’s huge data advantage, it can provide accurate matching for course providers and course demanders.

Table 3-1 Comparison of B2B2C OEP, B2C online school, knowledge-based pay

<table>
<tr><th></th><th>B2C online school</th><th>B2B2C OEP</th><th>Knowledge-based pay</th></tr>
<tr><td>Definition</td><td>A carrier where institutions focuses on self-operated education.</td><td>An open carrier that aggregates courses in multiple fields</td><td>A third-party platform focuses on the aggregation of content and fragmented light knowledge sharing.</td></tr>
<tr><td rowspan="3">Generality</td><td colspan="2">With the goal of carrying out skills training and online education, move the traditional teaching scene online</td><td></td></tr>
<tr><td></td><td colspan="2">An aggregation and intermediary platform for open third-party knowledge content, linking both content providers and content receivers.</td></tr>
<tr><td colspan="3">Belong to information consumption, and the whole process involves the process of purchasing and using information products and services (State Information Center, 2017).</td></tr>
<tr><td>Teaching entity</td><td>Teaching and research team of the platform</td><td>Independent teachers, educational institutions, Internet celebrated teachers</td><td>Internet celebrated teachers</td></tr>
</table>

Scope of knowledge	Relatively vertical education	A wide range of courses in the vertical field.	Light knowledge of various social experiences and opinions
Course consumption	Platform is in charge of pricing, so course fees are direct income. The course price is higher.	The platform assists in pricing, and relatively high commission income, and unit price.	Relatively low per customer transaction
Ways of dissemination	Heavy models, combine multiple forms of education with the live/recording course as the core, and some combined with offline education services	Heavy models, combine multiple forms of education with the live/recording course as the core.	Light mode, simply use some form of education, such as text, images, community, audio, etc.
Course system	Mature and structured curriculum.	Mature and structured curriculum.	Fragmented way of transferring knowledge.
Learning purposes	Targeted education investment, which is aimed at users who need to achieve their educational purposes.	Targeted education investment, which is aimed at users who need to achieve their educational purposes, while some users need light knowledge.	Diverse needs for knowledge, but there are also users who need light knowledge.

The differences and identification of these 3 kinds of OEP has been clarified Table 3-1. In this study, the B2B2C OEP is defined as the third-party education platform on the Internet that links the educational resources to both the supply and demand sides to provide technical support and services for online education implementation and content realization. At the same time, the demand side of educational content is referred to as “users” in short, and the B2B2C OEP is referred to as “platforms” in short. Online education and the development of new technologies on the Internet, the transformation of educational concepts, the escalation of user education needs, and lifestyle changes are closely related. With the continuous expansion of Internet education and the increasingly stable business model, the deepening of user learning needs, the awakening of consumer awareness and the improvement of spending power, China’s online education (online learning) has ushered in the era of intelligent education featuring vertical segmentation of learning content, the diversification of learning methods, open and sharing learning content, and the profits realization of educational resources.

3.3 Overview of global OEI Development

3.3.1 Overview of foreign global OEI Development in the United States, the United Kingdom

Docebo (2016) showed that by the end of 2016, the value of the online learning market in the United States exceeded 27 billion US dollars. The concept of online learning is beginning to be accepted by users. In addition, as the network and mobile terminal devices become popular, the online education market will continue to grow in the next few years. All the above factors have a positive impact on market size, boosting the growth of online education demand, and the industry growth in the next few years.

BestColleges.com (2018) indicated that 40% of respondents plan to increase the online education expenditure in the near future, 79% of online education students and 76 % of alumni believe that online education is “better than” or “equal to” traditional school education, while 57% of schools say employers have similar feelings, and online education continues to show an upward trend in the United States.

Table 3-2 History of online education development

Time	Stage	Representation	Characteristics
Before 1990	Traditional education	Correspondence, slide/projector, radio/television, recording/videotape	Education informationization and new teaching methods are applied in classroom education, which improves the efficiency of education.
1990-2000	Digitized education	Electronic computer, multimedia courseware, internet, distance learning	The popularity of PC computers and the Internet, digital technology is applied to the process of education and teaching. China has approved 68 universities to become pilots for modern distance education.
2000-2010	Internet + education	Learning community, video courseware, online school	The Internet learning community, teaching videos and other methods have developed rapidly. New Oriental, Hujiang and other network schools are running their business online.
2010-2013	Mobile + education	Recording/live class, MOOC, mobile education, big data application	Recorded and courses that needs to be paid form a stable business model. Live courses appear. Mobile education begins to develop. MOOC with high-quality in universities rises in China.
2013 till now	Intelligence + education	Knowledge payment platform, B2B2C platform, artificial intelligence application	A knowledge-based payment platform with “light knowledge” emerged. B2B2C OEPs, which integrates online schools, MOOC, live broadcast, and

	knowledge payment, has become a new model.

Source: iResearch (2018) and FIRI (2019)

The forms of online education in the United States include the MOOC, distance education, and Open University. The MOOC market in the United States is closer to the size of China's OEPs. In terms of the selection of nouns, "online education" and "e-leaning" are to depict online education from different angles. This study uses the OEP as the research object, and since the meaning of the above nouns is not fundamentally different, synchronized searching with these key words were also done.

Table 3-2 indicates the history of online education development. Born in the United States, the form of online education, MOOC, has registered 160,000 users (Li, 2014) in more than 190 countries in 2011. Professor Sebastian at Stanford University developed *Introduction to Artificial Intelligence*, which gained popularity rapidly. It also gave birth to the Udacity online course. Shortly after, professors Wu Enda and Daphne at Stanford University co-founded the online free course, Coursera, in 2012. In April, the number of students reached more than 1 million. Later, more than 100 famous universities including Princeton University, Stanford University, California Institute of Technology, University of Michigan and the University of Pennsylvania joined the Coursera OEP and offered free online courses. In May 2012, MIT and Harvard University jointly launched the edX, network online teaching program. The first Electronics and Circuits course they initiated had more than 120,000 students registered. By the end of the autumn in 2012, over 370,000 students registered the courses, and hundreds of well-known universities around the world have joined edX. In 2012, various MOOC courses were rapidly spread and developed. The New York Times called 2012 the "MOOC first year". MOOC began to rise on a global scale. The arrival of MOOC has made people realize that the combination of network and education is closer. It is firmly believed that this imposes a huge impact on the development of higher education and even change the pattern of higher education. In the past, only a few outstanding students had the opportunity to participate in world-class universities, not only because of the soaring tuition fees, but also because of the limited number of students enrolled. Now, with the advent of the MOOC, as long as the Internet is connected, anyone can enjoy the quality education content of the world's top universities for free anywhere and anytime. Therefore, MOOC quickly attracted widespread attention of both higher education and the general public (Shu, 2016).

USDE (2014) pointed out that there would be more useful explorations of online learning communities to promote professional learning, and three stories about using online communities to improve educational outcomes have been listed. For example, Sherri mentioned that as a middle school teacher she used to offer day-to-day teaching, and then she always feels very upset and helpless when she encounters some of the problems in teaching. Then she was glad to join some online math forums and found some teaching methods that were valuable to her. Finally, she solved the problems that she encountered in teaching. The report also describes more explorations in the future on how to use information tools and OEPs to enhance teaching effectiveness (USDE, 2014).

Shah (2019) mentioned that the size of the MOOC in the United States has grown to more than 9,400 courses, with more than 500 certificates based on MOOC courses, and more than a dozen master's degrees. According to data collected by Class Central, approximately 23 million new students enrolled in their first MOOC course in 2017. This number is similar to the 23 million new students enrolled in the MOOCs in 2016. According to statistics, the total number of MOOC students is currently about 81 million.

Founded on April 23, 1969, the Open University of the UK is a world-class leading university that is flexible and innovative. The unique system there helps the Open University to have a better understanding of the needs of part-time students, so students can better balance their work and study. More than 2 million students have been educated at the Open University of the UK, including more than 300,000 graduate students. Now it is the largest university in the UK with 250,000 students at university (Open University, 2019).

Docebo Research Institute (2016) indicated that half of India's population is actually less than 25 years old. It is expected that India will face a shortage of 250 million skilled workers by 2022, so it is considered that India's education will rely heavily on online education. By the end of 2015, India is already the second largest online education market after the United States. Google and KPMG (2017) calculated that India's online education market would grow from approximately 1.6 million users in 2016 to 9.6 million users in 2021. Latin America is expected to achieve significant growth between 2016 and 2020. The share of online education market in Latin American is estimated at approximately 2.1 billion US dollars in 2016 and may continue to grow at a compound annual growth rate of over 14% in the next few years. According to Ambient Insight, revenue from mobile learning products and services in Brazil reached 333.3 million US dollars in 2014, a growth rate of 25.7%. By 2019, revenues surged to more than 1 billion US dollars. Brazil is also the fastest growing mobile learning market in Latin America. In recent years, some countries in Latin America have adopted MOOCs on a larger scale. Mexico and Brazil are 2 of the 10 countries with the highest usage rates of MOOC. Veduca is a Brazilian MOOC platform offering more than 300 free online courses in 21 areas. According to Ambient Insight, by the end of 2016, the US e-learning market exceeded $27 billion, and the US is also the largest consuming country of the online education, followed by Japan, South Korea, China, and India. According to data from Ambient Insight, the online education market in western Europe in 2016 was about 8 billion US dollars, while the eastern European market was about 1 billion US dollars. The largest consuming country in Eastern Europe is the Russian Federation, while the one in Western Europe is the United Kingdom.

3.3.2 Overview of China’s OEI

In September 1998, the Chinese Ministry of Education officially approved Tsinghua University, Beijing University of Posts and Telecommunications, Zhejiang University and Hunan University as the first batch of pilots for online distance education. Since then, China’s online distance education has entered a period of rapid development, and online education in Chinese universities has also took off, catalyzing the development of China’s OEI.

Shu (2016) proposed that China’s online distance education usher in a period of rapid development after 200: First, educational information technology, multimedia technology, including online video courseware, system for web-based online question and answer, were started to be applied, greatly improving the efficiency of education; Second, the Ministry of Education officially approved 68 colleges and universities as pilot institutions for the national modern distance education, the establishment of online education colleges, and issuing both online education qualification and degree certificate for students who meet the graduation requirements. The total scale of distance education accounts for more than 90% of the online market share of online education in China; Third, the online school represented by New Oriental was officially launched in 2000, marking the beginning of the traditional training school to enter the online education market and enriching the type of content provider in online education sector.

In 2012, MOOC swept the world, and Chinese universities began to join the MOOC building and practice in early 2013. Tsinghua University, Peking University, the University of Hong Kong and Hong Kong University of Science and Technology have joined the edX OEP. In 2014, Peking University, Fudan University, Shanghai Jiaotong University, National Taiwan University, The Chinese University of Hong Kong and the Hong Kong University of Science and Technology joined the Coursera platform. In June 2014, Fudan University, Shanghai Jiaotong University and Future Learn signed a memorandum to cooperate in building MOOC in London, according to which they provided quality courses on the platform. On the one hand, China has introduced foreign MOOC, and on the other hand, China is also trying to build a local MOOC OEP. For example, Xuetangx of Tsinghua University signed a cooperation agreement with edX to become the sole authorized partner of edX in China's mainland. Currently, Xuetangx has more than 120 MOOCs offered by universities on edX.

CINIC (2019) released that the number of online education users in China reached 201 million. In 2018, it continued to grow at a rate of 29% compared with that in 2017. ERCIEI (2019) calculated that the market size of China's OEI in 2018 exceeded 300 billion, at a growth rate of 45% comparing with that number in 2017. With the gradual maturity of the OEI and the rationality of venture capitals, it has become increasingly difficult for traditional offline education institutions to transform into online ones, and for new knowledge sharers who join education institutions for a short time to seek growth online. However, the B2B2C OEP provides opportunities and space for development for the above-mentioned two groups.

Since 2018, the investment and financing situation in China's online education market has been booming. Ni (2018), a reporter at Guangzhou Daily, put forward that despite prospering financing situation of OEP, a large number of online platforms are at a loss. Su (2019) pointed out that the New Oriental Net School, which was listed on stock exchange the 2019, still faces the urgent need to solve the problem of high customer costs, and its net profit was 36.2 million yuan from in June to November 2018, a year-on-year increase of -59.9%. The prospects of online education in China is not optimistic.

Although many companies in China's OEI are still losing money, five factors are still giving impetus to China's OEI entering motorway and these five factors are the popularity of the Internet, the continuous growth of the number of Internet users, the development of habits in electronic payment, favorable policies, optimistic views owned by venture capitals, and the continuous growth of demand. ERCIEI (2019) pointed out that the per capita consumption of online education in China is far less than the per capita investment in developed countries, such as Europe and America. Therefore, online education in China is still in the growing stage. With the increase in China's household disposable income, coupled with China's huge population base and the government's encouragement of fertility, China's online education market has a very broad space for development.

3.3.3 Analysis of typical China's OEP enterprises

Torch Center of China Ministry of Science and Technology (2017) pointed out that the concept of "unicorn enterprise" refers to start-ups that have fast development, few counterparts, and are investors' enthusiasm. The threshold is that the company's valuation needs to be larger than 1 billion US dollars after ten years of development. If the valuation exceeds 10 billion US dollars, the company will be called "super unicorn". Since the concept of "unicorn" was put forward, it has quickly gained recognition from many organizations in the global science and technology, and investment communities, such as Wall Street Journal, Fortune, Tech Crunch, and CB Insights. The Torch Center (2017) also clarified the standards of Chinese unicorn enterprises:

(1) Enterprises registered in China with legal person status.

(2) The establishment time is not more than ten years (established in 2007 and after).

(3) Obtain private equity investment and has not been listed by IPO.

(4) A unicorn needs to meet the conditions of (1) (2) (3) and whose valuation exceeds 1 billion US Dollars.

(5) A super unicorn needs to meet the conditions of (1) (2) (3) and whose valuation exceeds

$10 billion.

According to the statistics of the online education “unicorn” by ERCIEI (2019), 11 “unicorns” were born in the OEI in China. CCtalk is a real-time OEP of Hujiang. It provides independent online education tools and platforms for independent knowledge instructors and sharers, providing users (knowledge seekers) with rich knowledge content and online community environment for learning. The meaning of CC is the combination of “content” and “community”. It is a B2B2C OEP overlapping with knowledge sharing and online education. There are four major categories of education, language, vocational education, education for students in kindergarten, primary and middle schools, and art. It covers more than 50 sub-categories, including English, Japanese, Korean, civil service examination, vocation, biology, Olympics, physics, music, overseas study tour, cooking, and IT training. They model of online live classroom on CCtalk can be used to have online communication with students around the world. The learning community restrains students from learning alone. CCtalk (2019) claimed that there were more than 30,000 online teachers and thousands of high-quality content and teaching institutions on CCtalk, with a total of 850,000 courses and more than 10 million students. In 2017, the business volume of CCtalk achieved exponential growth. The average growth rate of platform gross merchandise volume exceeded 150% for three consecutive quarters. At the same time, the number of daily active users, number of users and flow of users increased by 8, 10 and 30 times compared with those figures in 2016 (CCtalk, 2019).

Tencent Classroom is a B2B2C OEP owned, controlled and operated by Tencent. Tencent Classroom is a neutral platform and service provider that provides course publishers with neutral network services such as information storage and links to neutral technical support services for course publishers to publish, operate and promote independently on a neutral platform, at the same time the platform can meet the users’ demand of learning online and knowledge acquisition. At present, Tencent Classroom has six major categories on its website, IT Internet, design and creation, language and studying abroad, vocational certification, higher school education and entrance examination for post-graduation, and interest and daily life. Each category is furthered divided into different segments. After more than four years’ hard work and development, Tencent has provided more than 100,000 online education courses to 300 million users.

NetEase Cloud Classroom is an online practical skill learning platform created by NetEase. The platform was officially launched in December 2012. It provides many high-quality courses for learners. Users can arrange their learning plan and deign according to their own level. The purpose of NetEase Cloud Classroom is to provide a thoughtful one-stop learning service for every learner who really wants to learn practical knowledge and skills. Based on practical requirements, NetEase Cloud Classroom selects various courses and cooperates with several authoritative education and training institutions. The number of courses on this platform has exceeded 10,000 and the total number of course hour has exceeded 100,000, covering more than ten categories, such as practical software, IT and Internet, foreign language learning, living and home, hobbies, workplace skills, financial management, exam certification, primary and secondary schools, parent-child education, etc. In this way, a practical platform has been created for users, covering their life, career, entertainment and other dimensions. By the end of December 2017, the number of users on NetEase Cloud Classroom has exceeded 55 million (NetEase, 2018). At present, the paid courses on NetEase Cloud Classroom account for 70% of all their online courses, and there are more than 5,000 lecturers and institutions partnering with the platform (NetEase, 2018).

3.4 Chapter summary

This chapter describes online education, its business models, and an overview of online education development around the world. This research aims at studying factors influencing online PI, and the B2B2C OEP is a professional e-commerce website, so the B2B2C OEP should also have the characteristics of online education and e-commerce. The chapter first describes online education, then classifies the business model of the OEP, summarizes its characteristics, and depicts its development history and future trends. This chapter reviews the industry background and lays a solid foundation for the research on the factors affecting PI of user courses on China's B2B2C OEP.

Chapter 4: Research Design and Data Collection

4.1 Factors influencing users’ PI

In the construction of the model of factors influencing user’s intention to purchase courses on OEP, this study was based on the related theories of PV and PR, taking PU and PC as the consideration factors for the perceived benefits and perceived loss of buying online courses. This research also learned from previous researches results, and introduced time and space autonomy (TSA), course free trail (CFT), PEU and PR as the key factors that directly affect the users’ intention in purchasing online courses.

ERCIEI (2019) pointed out that no limitation of the place and time of study becomes an important advantage of online education. This advantage breaks the limitation of time and space restrictions, better saving users time and cost, and allowing students to be independent in scheduling their time of study. Therefore, he of this research constructed a context variable of TSA to examine whether the autonomy of time and space of the course affects users’ decision in purchasing courses on OEP.

“Purchase Intention” in buying online course is the core dependent variable of the model, which is used to reflect the user’s willingness to purchase the course. PV, TSA, FCT, PU, PEU, PR, PC and WM are 8 explanatory variables that potentially affect the willingness of users to purchase courses. In addition, due to the particularity of buying online courses on China B2B2C OEP, this study selects age, education and income level of users as control variables to study their impacts on the user’s intention in purchasing online courses.

Therefore, utilizing the PV theory and previous research results, as well as combining the courses consumption scenarios on Chinese B2B2C OEP, he builds a model of users’ intention in purchasing courses on OEP with 8 factor variables, which is shown in Figure 4-1.

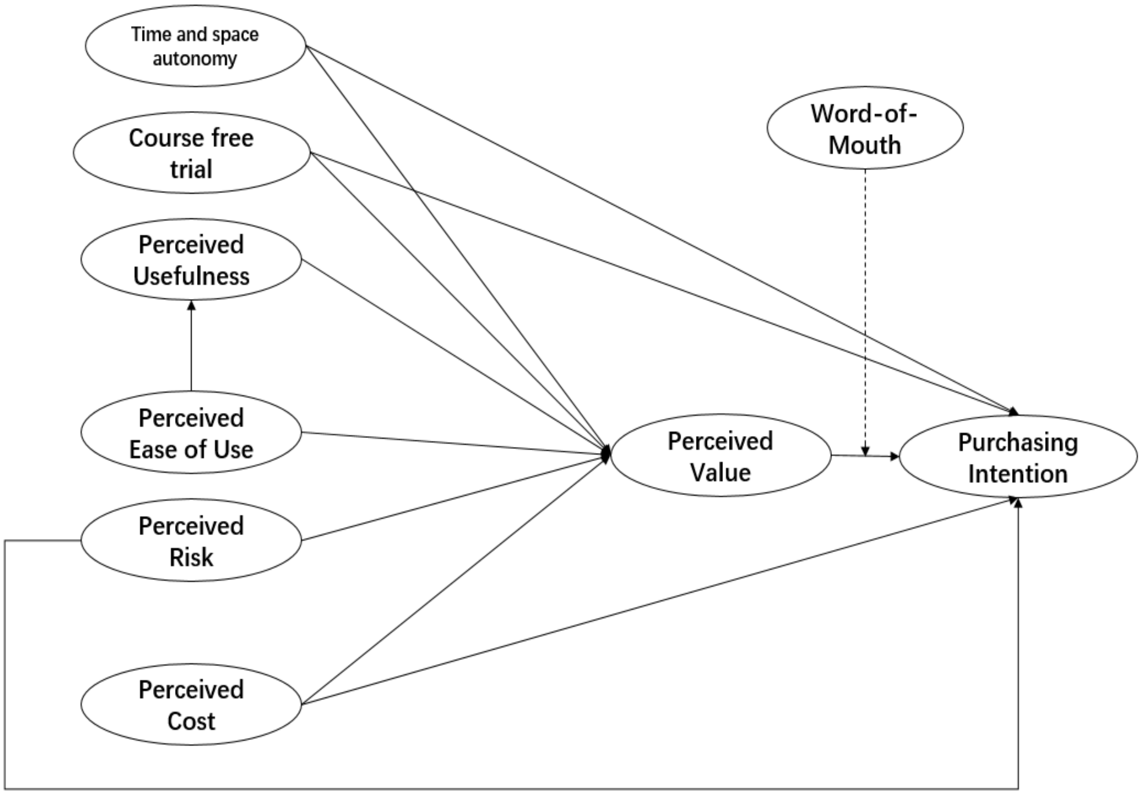

Figure 4-1 The model of PI of users on B2B2C OEP to buy courses

4.2 Variable constructs and research hypotheses

“Purchase intention” is the dependent variable of this model in which the model variable consists of four parts, including the independent variable, the mediation variable, the dependent variable and the moderation variable. The independent variables are TSA, CFT, PU, PEU, PR, and PC; the mediation variable is PV; and the moderation variable is WM. Due to the particularity of the course consumption scenarios on the Chinese B2B2C OEP, this study includes the characteristics and demographic attributes of users on Chinese B2B2C OEP as control variables, and these attributes are age, education background, and income level of users.

The specific variables are shown in Table 4-1.

Table 4-1 Summary of variables of this research

Type	Variables
Dependent variable	PI
Mediator	PV
Independent variable	TSA, CFT, PU, PEU, PR,PC
Moderator	WM
Control variables	Age, education, income

4.2.1 Course PI

"Purchasing Intention" is considered a decision-making process and refers to the possibility that consumers have purchased or attempted to purchase a product or service (Fishbein & Ajzen, 1975; Bagozzi & Burnkrant, 1979; Dodds, Monroe, & Grewal, 1991; Feng, Mu, & Fu, 2006; Xu, Zhang, & Dong, 2018; Lin & Qu, 2019). In this research, PI of users on B2B2C OEP to buy courses refers to the probability of purchasing the course on B2B2C OEP, which is the core dependent variable of this research model since all other factors indirectly affect the user's behavior through PI.

As the decisive factor before putting purchase behavior into action, PI is the necessary process for the next step of action. The stronger the PI is, the higher probability will be that the user will purchase the corresponding product in the future, and vice versa. Kim, Xu, and Gupta (2012) found through their research that price and trust are important factors influencing users' online purchasing decisions. Previous studies concluded that users' PI in different consumption scenarios was affected by different factors, and most studies confirmed that there was a significant positive correlation between PV and PI (Zeithaml, 1988; Ravald & Grönroos, 1996; Han & Tian, 2005; Feng, Mu, & Fu, 2006; He, 2015; Wang, 2018). PC, PR, perceived trust and other factors also affect the user' s PI. Hong, Zheng, and Zhou (2019) found that users that the potential factors affecting users' intention to pay for answering questioned they have proposed include social impacts, task pressure, curiosity, perceived interest, and ease of technology use through the research on online Q&A community.

4.2.2 PV

In the context of this study, PV refers to the comparison conducted by users between the perceived benefit and PC that the product or the service brings. When the perceived benefit is greater than PC, the customer has positive PV (Monroe, 1973). Positive PV increases consumers' willingness to buy. Similarly, when the benefit perceived by the consumer is greater than PC, the customer will have a willingness to purchase, and the greater the PV is, the higher PI will be.

In terms of the relationship between PV and PI, many researchers have confirmed the positive impacts of PV on consumers' PI in previous studies (Zeithaml, 1988; Grewal, Monroe, & Krishnan, 1998; Wang, 2007; Zhong, 2013). Therefore, when constructing the theoretical model of the factors influencing the PI of courses on education platform, he regards the user's PV of the paid course as a key factor affecting the user's PI. He (2015) found that PV of consumers on the comprehensive B2C online shop has a significant and positive impacts on their PI. From the research on the relationship between the two dimensions of PV and PI, it could be found that: both the functional value and the emotional value have a significant and positive impacts on the consumers' PI. From the perspective of the level of impacts, the functional value is the priority in consumers' consideration with emotional value next to it. It can be explained that for online consumers, the first purpose of online shopping is to buy goods, and second purpose is to enjoy the fun brought by online shopping. Consumers' PI depends on the perception of value. When purchasing goods or services in an online store, the greater PV the customer has, the greater PI the customer will have, and vice versa. It can be illustrated that improving the functional perception of online products or services that the consumers can access to increases their PI, and the improvement of emotional perception also increases their PI. Pang (2018) concluded that PV also positively affect the user' s willingness to pay. Hong, Zheng, and Zhou (2019) found that the quality, quantity, valence of online reviews and the credibility of online reviewers have a positive impact on college students' PI, indicating that the quality of online reviews of higher quality deliver greater PV to users. It was also found that the PV significantly and positively affects users' PI, and PV partially mediates the online comment and PI. Therefore, improving both the functional and emotional value of online products and service perceived by consumers is an effective way to enhance consumers' PI.

Based on the analysis above, the hypothesis proposed in this study is as follows:

Hypothesis 1 (H1): PV has positive impacts on PI.

4.2.3 WM

In the context of this study, WM refers to the user's perceptions of the course, the online comments of the instructor, and the impacts of WM on PI. WM regards as an important factor to affect marketing and consumer buying behavior (Huang & Zhu, 2003; Chen, Wu, & Zhang, 2017; Wang, Li, & Wang, 2017). WM delivers relevant information of products and services to the consumer, and it helps other consumers make purchasing decisions.

Park, Lee, and Han (2007) believed that online commentary plays a vital role in affecting consumer decision-making through their empirical research. The quality and quantity of online reviews have positive impacts in consumers' PI. Lee and Youn (2009) argued that positive reviews have a positive impact on consumer's willingness of recommendation and purchase, while negative reviews have negative impactss. During the study of the consumer's reading motivation and the search for online WM on online consumption platform, Hennig-Thurau and Walsh (2003) found that consumers read other consumers' evaluations of relevant products while they shop online, and they help them save time and make better decisions.

Chinese scholars have also confirmed that online WM has a significant impact on consumers' purchasing behavior in relevant researches, and positive online WM of goods or services have positive impacts on customers' PI in the context of online shopping (Bi, 2009; Huang & Lao, 2013; Li, 2015). Negative online WM has a negative impact on purchasing intention (Bi, 2010; Guo, 2015; Zhang, 2017). Wang (2017) divided the PV into three dimensions, social value, emotional value and functional value in the research of the PI of imitation brand, and it can be found that all the three dimensions of PV positively affect the user's PI of imitation brand. Pang (2018) found that the evaluation and WM of the course has a positive impact on the user's PI. Chu (2018) divided customer PI into three dimensions: social value, emotional value and functional value, and concluded that PI of consumers of the legacy brand is positively affected by PV.

Based on the analysis above, the hypothesis proposed in this study is as follows:

Hypothesis 2 (H2): WM positively moderates the impacts of PV on PI.

4.2.4 PR

In this study, PR refers to the potential risks that buying the course bring to the consumer. Since the buying behavior is before the use the learning of the course, the potential risks may be caused due to the lack of comprehensive understanding of the course, the absence of the policy of return of goods for no reason within 7 days, and the lack of understanding of the content and quality of the course. On the one hand, without fully understanding the quality and content of the course, users may worry that learning course cannot help them achieve their learning expectation, causing their concern that spending money to buy the course may not be worthy. On the other hand, because the course is normally a non-returnable virtual product, and the user may not have enough time and energy to complete the entire course, users may worry that the time and money they devote into the courses can be converted into sunk costs.

Bauer (1960) first proposed the concept of PR, often referring to the subjective judgment of the individual on the risk characteristics and the severity of the risk, which is the uncertainty about the results of the decision-making, and severity of the possibility of making wrong decisions. Ji (2013) argued that perceived benefits, purchase costs and PR are factors directly influencing user's PI, and PR has a negative impact on the user's PI in the study of consumers' intention to purchase in the context of online consumption. Zhong (2013) took perceived product quality, perceived website service quality, purchase cost and PR as antecedent variables of online consumers' PV, and this empirical study found that all these four factors have an impact on consumers' PV and PI. Wang (2013) studied factors influencing users' intention in buying APPs on mobile app store, and in the empirical analysis, it is also found that users' PR has a significantly negative impact on PI. Wang (2016) divided PV into functional value, social value and situational value to explore the relationship between PV and use intention. After verification, it is found that both social value and situational value positively affect use intention, while PR negatively impacts users' situational value, functional value and use intention. Wang (2017) based on PV theory, took imitative brands as research objects, and found that both PC and PR negatively affect PV, while PC and PR have a negative impact on PI of imitation brand. Xiang (2018) found that users' PI and perceived financial risks, service risks, time risks, social risks and functional risks all have negative impacts, which means that when consumers perceive greater risks, their PI will be undermined. On the contrary, when consumers perceive milder risks, their PI will be more robust. Cui (2019) divided PR into product risk, financial risk, psychological risk, service risk and system risk when researching on online impulsive PI, finding that the five dimensions of PR all impose negative impacts on online impulsive PI.

Based on the analysis above, the hypotheses proposed in this study are as follows:

Hypothesis 3 (H3): PR has negative impacts on PI.

Hypothesis 4 (H4): PR has negative impacts on PV.

4.2.5 PC

In the context of this study, PC refers to the perceptions of the course price of OEP and the cost of online learning when the user of OEP makes the final purchasing decision.

When conducting the study of PC, Zeithaml (1988) proposed that perceived loss includes the PC which refers to things that users have to pay and can be perceived when using a product. Dick and Basu (1994) divided the PC which refers to the cost perceived by consumers in the payment process mainly into time cost, money cost, and cognitive cost. The time cost refers to the amount of time that the consumer perceives for the payment. The money cost refers to the amount of money that consumer perceives for the payment. The cognitive cost refers to the amount of cognitive resource that consumer perceives for the payment. The cognitive cost is mainly due to the unskilled mobile payment operation (accepted by new technology) or the risk during the payment process. Rabinovich, Knemeyer, and Mayer (2007) suggested that PC depends on the efforts spent in the transaction and all transaction-related activities.

Wang (2016) in the research of factors influencing the users' willingness of WeChat payment, found that improving product technology is in favor of reducing PC and increasing PI. Wang, Li, and Wang (2017) based on the user value acceptance model is under the automobile new media environment, the empirical analysis of the questionnaire and the structural equation model shows that the information PC negatively affects the PV. Song (2018) based on the theory of PV and expectation confirmation theory to explore the internal mechanism that affects the continuous use of online knowledge payment by users, and finally found that the hypothesis of PC negatively affects PV is verified. Dong, Zhou, and Mao (2019) measured the PV of users from perceived benefit and PC. The study shows that better privacy security and feedback are timely helps to reduce PC and enhance user's PV.

Based on the analysis above, the hypothesis proposed in this study are as follows:

Hypothesis 5 (H5): PC has negative impacts on PI.

Hypothesis 6 (H6): PC has positive impacts on PV.

4.2.6 PU and PEU

In this study, PU is primarily used to measure the perceived benefit of a user when purchasing a paid course. It refers to the usefulness of the paid courses perceived by users compared to free courses. PEU refers to the perceived assessment of whether the OEP is easy to use.

Davis (1986) proposed the TAM that consists of six variables: external variables, PU, PEU, attitude toward using, behavioral intention to use, and actual use. TAM is mainly used to explain and predict the acceptance of users' continuous use of information systems. Based on the theory of rational behavior, TAM proposes two concepts, PEU and PU. Among them, PEU mainly refers to the user's subjective ease of use of the information system, and PU mainly refers to the subjective performance improvement of using the information system. At the same time, Davis (1986) believed that PU and PEU can replace "subjective norms", so the model excludes "subjective norms" and its corresponding influencing factors "normative beliefs" and "compliance motivation". Davis (1989) further proposed whether the user adopts the new system depends on the user's behavioral intention to use that is affected by the attitude toward using that is determined by PEU and PU together. Liu (2016) through her research on the factors affecting the intention to pay for online education, set forth that PU and PEU both positively affect the user's PI. Yang, Jiang, and Ma (2017) took consumers' intention to purchase online cultural products as the research object based on PV, discovering that users' PU significantly and positively affects PV and PI, and PEU significantly and positively affects users' PV. Fang, Lu, and Liu (2018) found that users' PU positively affects PV in the empirical study of users' intention to pay for knowledge in virtual community. Li and Wang (2019) studied how the social media promote online purchase behavior based on TAM, from which it was found that PU positively affects PI, and PEU positively affects PU. At the same time, the positive impacts of PEU on PI has also been partially confirmed, and this conclusion is similar to the results of TAM-related studies.

Based on the analysis above, the hypothesis proposed in this study are as follows:

Hypothesis 7 (H7): PU has positive impacts on PV.

Hypothesis 8 (H8): PEU has positive impacts on PV.

Hypothesis 9 (H9): PEU has positive impacts on PU.

4.2.7 CFT

In this study, CFT is a new factor variable combined with the situation of online education to reflect the user's perceived impacts of the CFT on OEP on their purchasing decisions (Li, 2016). Jiang (2018) suggested that the online training platform provide opportunities of CFT to gain more attention and sales opportunities. Whether the OEP supports course trial and the user's evaluation of the course trial affect the users' trust and their purchase decision. (Gao, 2018; Xu, Zhang, & Dong, 2018). Li, Zhang, and Hu (2019) argued that the attractive trial information has a positive impact on the user's intention to purchase. Based on this, this study believes that if the paid course of the OEP supports CFT, and the quality of CFT can meet the user's expectations, their PV and PI will be enhanced, and the probability that the course will be purchased may be higher.

Based on the analysis above, the hypothesis proposed in this study are as follows:

Hypothesis 10 (H10): CFT has positive impacts on PI.

Hypothesis 11 (H11): CFT has positive impacts on PV.

4.2.8 TSA

In this research, TSA means that the OEP provides users with a environment where the time and space of learning is not limited, therefore the course that can be purchased anytime anywhere. TSA is a unique advantage of the mobile Internet. Lee (2005) also confirmed that the ubiquitous nature of mobile commerce has a positive correlation with consumer perception trust. Kleijnen, Ruyter, and Wetzels (2007) confirmed from a time perspective that it has a positive correlation with consumers' PV of mobile services. Yang, Zhang, and Man (2012) also found that mobile Internet breaks time and space restrain. The convenience of the user has a significant impact on their PV. Fu (2013) proposed that the online platform, such as Weibo, has a huge number of users due to its autonomy. Users can enjoy the convenience of self-learning when using the mobile Internet (Yang, 2016; Li, 2016), saving their time and effort. Xuan, Dai, and Lin (2018) found that the feature of beyond the limits of time and space has a greater effect on promoting the purchasing behavior of young people in APP marketing. TRI (2019) mentioned that the independent choice of time and space has brought great convenience to users, so that users can make full use of their fragmented time to learn. It was also reported that TSA is one of the important factors to choose online vocational education platform for course learning (TRI, 2019).

Based on the analysis above, the hypothesis proposed in this study are as follows:

Hypothesis 12 (H12): TSA has positive impacts on PI.

Hypothesis 13 (H13): TSA has positive impacts on PV.

4.2.9 Relationship between control variables and PI

In this research model, individuals with different situations have a gulf in their willingness to purchase OEP courses. Therefore, this study also explored whether users with different attributes have significant differences in their intention to purchase courses on OEP courses. Fan (2015) concluded that users of different ages and education levels have significant differences in their intention to donate charity through questionnaires and empirical analysis. Chen (2018) found that the user's income positively affects their PI while the user's age negatively affects their PI through studying Vietnam users' intention to purchase online. TRI (2019) proposed that highly educated users have clear goals and judgments on the choice of courses, so high-education users can generate prominent and pronounced value for online professional education platform. At the same time, it was also proposed that the proportion of users aging over 40 years old is significantly lower than the proportion of users younger than 40 years old.

Based on the analysis above, the hypothesis proposed in this study are as follows:

Hypothesis 14 (H14)：Users with different attributes have differences in their intention to purchase courses.

1) Hypothesis 14 (H14a)：Users' age has negative impacts on PI.

2) Hypothesis 14 (H14b)：Users' education has positive impacts on PI.

3) Hypothesis 14 (H14c)：Users' income has positive impacts on PI

In summary, this study proposes 16 research hypotheses and constructs hypothetical model figures as shown in Figure 4-2.

In order to better verify the scientificity and hypothesis of this research model, a total of 16 research hypotheses were proposed in this study as shown in Table 4-2.

4.3 Research design

4.3.1 Questionnaire design

This research study adopts the empirical research method to obtain the data of the interviewees through questionnaire survey, so as to test the hypothesis model. In order to ensure the reliability and validity of the questionnaires issued, the steps for designing the questionnaire are as follows.

(1) Based on the research questions and research purposes, this study is based on the constructed theoretical model, he extensively read domestic and foreign literature in related fields for scales consistent with the meaning of the conceptual variables involved in this research model. Since scales used in this study are mainly from the English literature which needs to be translated into Chinese at the outset and then translated back into English to avoid tampering with the original meaning measured by original items.

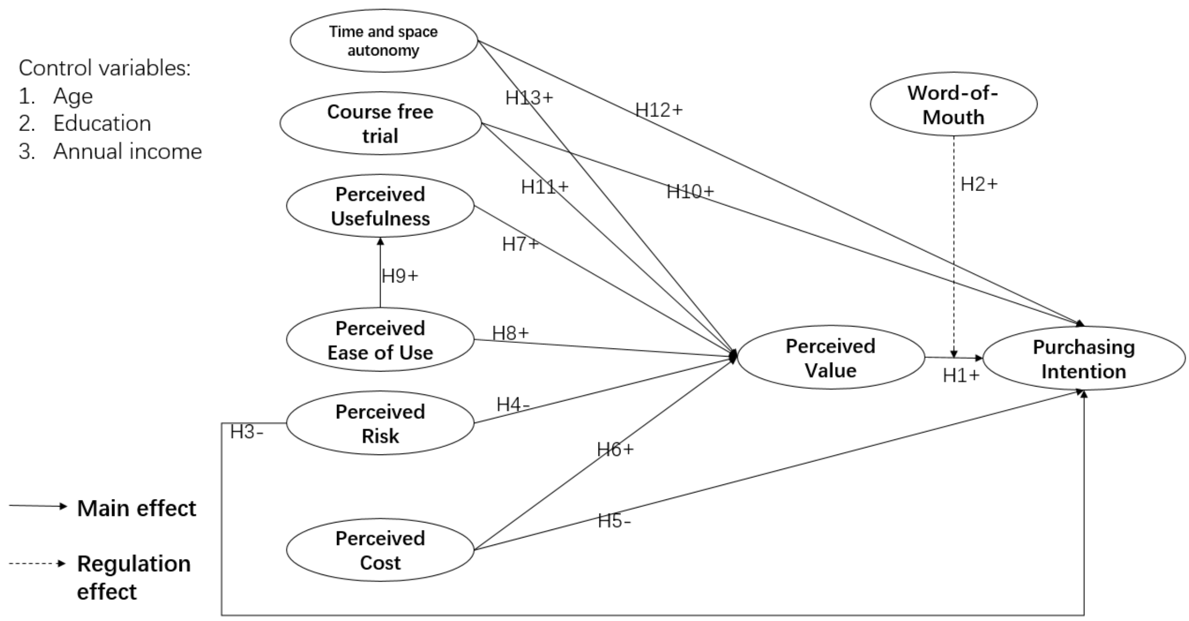

Figure 4-2 The whole mode l of PI of users on B2B2C OEP to buy courses

(2) Considering the specific research background of users on OEP, he first conducted small-scale interviews with some users to understand the uniqueness of the specific research background. Based on the matured scales and pre-investigation interviews, the relevant measurement items were adjusted to better fit specific research scenarios.

(3) After the formulation of initial questionnaire, he invited several experts experienced in online education, scholars in relevant field, mentors and students to evaluate the measurement items in the questionnaire, so that the problem statement is more in line with academic norms and life practices. The author also invited a small number of interviewees to conduct a formal questionnaire survey before issuing the questionnaire to confirm that the questionnaire has good

reliability and effectiveness.

(4) Taking into account the special research background of the B2B2C OEP, this study issued and recycled the formal questionnaires in the form of electronic questionnaires.

Table 4-2 Hypotheses summary

Hypothesis No.	**Research hypothesis**
H1	PV has positive impacts on PI.
H2	WM negatively moderates the impacts of PV on PI.
H3	PR has negative impacts on PI.
H4	PR has negative impacts on PV.
H5	PC has negative impacts on PI.
H6	PC has positive impacts on PV.
H7	PU has positive impacts on PV.
H8	PEU has positive impacts on PV.
H9	PEU has positive impacts on PU.
H10	CFT has positive impacts on PI.
H11	CFT has positive impacts on PV.
H12	TSA have positive impacts on PI.
H13	TSA have positive impacts on PV.
H14a	Users' age has negative impacts on PI.

H14b	Users’ education has positive impacts on PI.
H14c	Users’ income has positive impacts on PI.

4.3.2 Questionnaire structure

The questionnaire consists of three parts.

The first part is a survey of the basic information of users on OEP. Questions in this section were designed for information including their frequently used OEPs and the condition of how they used them.

The second part is the characteristics of the basic demographic variables of the interviewees, such as gender, age, education level, monthly income, occupation. Information of this part can reflect the individual and group characteristics of the research object as well as the control variables of the model more comprehensively and intuitively.

The third part is the investigation of the factors influencing users’ intention in purchasing courses on OEP. Measurement items in the part are meant to reflect conceptual variables in the model, TSA, CFT, PEU, PU, PR, PC, PV and PI.

4.4 Scale development and questionnaire design

4.4.1 Scale development

In order to validate the path hypotheses about factors that affect users’ intention in purchasing courses on B2B2C OEP, he based on the literature review and previous researches, and considered the situation of buying courses on the B2B2C OEP, as a result of which he decided to adopt the method of literature review and content analysis to design and develop scales for the measurement of latent variables.

The author first reviewed the results of previous researches about factors affecting PI of paid courses on OEP, summarized mature measurement scales related to the latent variables in the theoretical model, and combined the situation of OEP. Finally, a mature measurement scale including potential variables containing PV was finally readily accessible.

After completing the development of the preliminary measurement scale, he invited five doctors or scholars who have done similar empirical research, three industry experts engaged in online education companies, and five users with experience about B2B2C OEPs to form an expert team of measurement scale design. The expert team weighed and studied the concept, definition and scope of each potential variable elaborately after several rounds of discussion, and thought over the measurement content, wording and problem description of the initial scale. According to their feedback, the scale was revised to avoid ambiguity in meaning, and some items that could not effectively reflect the construct of latent variables were deleted after careful consideration. As a result, the final measurement scale was finalized, which can be seen in Table 4-3. This questionnaire used the 7-piont Linkert scale to conduct the questionnaire survey that extends from one end of the spectrum, an extremely positive attitude to the other end of it, an extremely negative attitude.

4.4.2 Questionnaire design and pre-investigation

Linkert (1932) improved the original scale and proposed the Likert scale. After designing the measurement index of each latent variable, the 7-point Linkert scale was used to design the questionnaire for each measurement index of the influencing factors of the B2B2C OEP user course PI. The initial survey questionnaire consisted of two parts: (1) the main purpose of the course and experience of purchasing the course; (2) the 7-point Linkert survey of 37 index items about the 9 potential variables.

The survey was conducted mainly by means of online questionnaire survey. The pre-investigation section collected 70 questionnaires from Wuhan University, University of Electronic Science and Technology, Zhejiang Vocational College of Business and Technology, and after cleaning unreasonable and invalid data, 63 valid questionnaires were obtained, with an effective recovery rate at 90%. In order to ensure the reliability and validity of the final data measuring the factors affecting users' PI of the OEP, the reliability analysis and exploratory factor analysis of IBM SPSS V24 were used to verify the reliability of the data after the pre-survey. In order to verify if the research obtained real feedback on consistency, consistency and stability from users, the Alpha model was used to obtain the cloned Bach coefficient.

The reliability analysis used Cronbach's alpha value as an indicator. It is generally considered that if the total correlation coefficient of an item is less than 0.5 and deleting the item can significantly increase the Cronbach's alpha of the entire scale, it is rational to delete the item. The analysis results showed that 9 common factors were extracted out of the 37 measures items, and the reliability test of the 9 factors is greater than 0.75, which indicates that the questionnaire has good reliability.

Validity analysis mainly refers to KMO, exploratory factor analysis, and confirmatory factor analysis. Through analysis, it was found that the KMO values of each variable were above 0.7. When the data analysis was carried out, it was found that the common factor variance extraction value of the WM measurement item, "I will refer to the relevant comment of the course before purchasing it" was less than 0.7. In order to ensure the final reliability and validity of the questionnaire, the item with lower factor load was deleted.

In addition to the reliability and validity, he also revised and improved the wording and description of items based on the feedback, and then formed a questionnaire containing 36 measurement items about factors that impose impacts on PI of courses on the B2B2C OEP which can be seen in the Appendix.

4.5 Data collection and processing

4.5.1 Determination of sample capacity

This study used the SEM to test the proposed hypothesis model. For the determination of sample size, Schumacker and Lomax (1996) proposed that when using SEM to conduct study, the number of samples should be between 200 and 500. Mueller (1997) considered that it is better that the number of samples for SEM is over 200. Sun and Zhou (2005) considered that the sample capacity of at least 10 times that of each observed variable. A total of 36 measurement items were included in the study. Considering that there may be invalid questionnaires during the data collection process, the sample size of this study is more than 360.

The main research subjects of this research are the users who have experience in using OEP in China. Respondents who have not used the OEP are considered to be ineligible for the target sample. Therefore, this study sets the first question of the online questionnaire as the screening item. For the respondents who never use the OEP, the questionnaire was directly ended after question one, which can filter the subjects who do not meet the requirements, and select out the target subjects who meet the requirement of the questionnaire. In this way, enough valid questionnaires can be obtained, laying a scientific foundation for further data analysis. Whether the respondents have experience in using OEP is also considered to ensure the accuracy of research object.

Table 4-3 The models of the factors affecting PI of the course for B2B2BC OEP users and measurement scales

Potential variables	**No.**	**Measurement scales**	**Reference**
Perceived Value	PV1	Purchasing an online course is worthwhile compared to the money I pay.	Sirdeshmukh, Singh, and & Sabol (2002)
	PV2	Purchasing an online course is worthwhile compared to the time I spend.	
	PV3	Purchasing an online course is worthwhile compared to the energy I spend.	
	PV4	I think purchasing online courses is valuable and meaningful.	
Word-of-Mouth	WM1	I will refer to the relevant comments of the course before purchasing the online course.	Park, Lee, and Han (2007), Lee and Youn (2009), Zhong (2013)
	WM2	The review information of the online course in comment area is more realistic	
	WM3	The review information of the online course in comment area is more reliable.	
	WM4	The review information of the online course in comment area is more objective.	
	WM5	The review of the course will affect whether I purchase a paid course.	
Perceived Risk	PR1	When I purchase an online course, I will worry that the quality of the course cannot meet expectations.	Kim, Ferrin, and

	PR2	When I purchase an online course, I will worry that the course cannot achieve the purpose of learning.	Rao (2008), Shim, Eastlick, and Lotz (2000)
	PR3	When I purchase an online course, I will worry that I cannot stick to the course.	
	PR4	When I purchase an online course, I will worry that the after-sales service cannot be guaranteed.	
Perceived Cost	PC1	I think the online course is relatively expensive.	Kankanhalli, Tan, and Wei (2005)
	PC2	High price is a barrier to my online course purchase.	
	PC3	Purchasing an online course will cost me more money.	
	PC4	Online courses do not shorten the time and energy of my knowledge learning.	
Perceived Usefulness	PU1	I think online courses can improve my learning efficiency.	Davis (1989), Ouyang (2014)
	PU2	I think online courses can improve my learning result.	
	PU3	I think online courses can help me achieve my learning goals.	
	PU4	I think online courses can make my learning easier.	
Perceived Ease of	PEU1	I can easily find the courses I need through the OEP.	Davis (1989), Ji

Use	PEU2	I can easily use the OEP for course learning.	(2013)
	PEU3	I can easily contact the provider of the online course.	
	PEU4	I can easily use the new features and new versions of the OEP.	
Course Free Trial	CFT1	Online courses that support free trials can help me make more informed purchasing decisions	Li (2016)
	CFT2	If the free trial of the online course reaches my expectations, my willingness to purchase will increase.	
	CFT3	If the form of teaching can attract me during the free trial, my willingness to purchase will increase.	
	CFT4	Whether the online course supports free trial will affect my willingness to purchase.	
Time and Space Autonomy	TSA1	When I study online, I can decide the learning content on my own.	Kleijnen, Ruyter, and Wetzels (2007), Roca and Gagné (2008), Yang (2016)
	TSA2	When I study online, I can decide the learning progress on my own.	
	TSA3	When I study online, I can decide the learning time on my own.	
	TSA4	When I study online, I can decide the learning place on my own.	
Purchasing	PI1	In the future, I will try purchasing a paid course on the OEP.	Kim, Xu, and

Intention	PI2	In the future, I will continue to purchase paid courses on the OEP.	Gupta (2012), Wang (2018)
	PI3	If the online course is what I need, I am willing to purchase it.	
	PI4	I am willing to recommend high quality online courses to friends.	

4.5.2 Methods of collecting data

After adjusting the initial questionnaire based on the results from the preliminary survey, he designed the finalized web-based questionnaire on the Questionnaire Star platform. The finalized questionnaire is mainly issued to users through QQ learning groups of OEP users, such as DC Academy, Himalayan FM, Maimai APP. With the coordination and assistance of the operation department of DC Academy, the online questionnaire was distributed through various channels such as the WeChat official account of DC Academy, official notification email of DC Academy, station letter of DC Academy, and its users' WeChat groups.

The DC Academy is positioned as the professional big data online learning platform. To encourage users on the platform to participate in the research, the operators of DC Academy have specifically planned and carried out coupons for this survey as rewards, in order to attract more users to participate in this survey. In this research, a total of 7416 emails and a total of 51,697 station letters were sent to invite users in DC Academy.

The period for the question issuing and collection lasted for more than 3 months (from January 24, 2019 to April 23, 2019). Due to the different rules on each platform, the time of issuing the questionnaire on different platforms was slightly different. There were 997 responses involved, of which 698 were submitted via WeChat, and 299 were submitted via mobile (or directly through the link). Among the 997 questionnaires, there were 729 users who have experience in using the OEP, and there are 268 users who have no experience in using the platform. In this survey, users who have experience in using the OEP have also been asked whether they have purchased course on the OEP. 436 of 729 users have purchased courses on the OEP, and 293 have not purchased any online course.

4.5.3 Data cleaning

After the investigation, he downloaded 997 sample data from the Questionnaire Star platform to facilitate further data processing and analysis. Since the first question of the questionnaire asks users whether they have experience in using the OEP, users without relevant experience are not allowed to proceed the survey at the first question, and users with relevant experience can continue to fill out the questionnaire, so as to further guarantee the quality of the data from questionnaires. In 997 questionnaires, a total of 729 users with experience in using the OEP were received, and 285 users who did not have experience in using the platform automatically submitted the questionnaire right after the first question.

The function of the Questionnaire Star platform mandate that questionnaires are not eligible for submission unless all questions are responded. This function automatically guarantees that the 729 questionnaires done by users with experience in OEP are completed without any missing item. In addition to that, he cleaned the 729 original questionnaire data to exclude non-applicable sample data to ensure that the sample data used for empirical analysis were filled in with high quality.

Since this survey questionnaire contains two parts with a relatively high number of questions, it usually takes 3 to 10 minutes to complete the questionnaire according to the preliminary investigation. Therefore, the questionnaires that were responded with less than 120 seconds and more than 720 seconds are deemed as unsatisfactory response. Questionnaires filled in with too little time are not taken serious by users. Therefore, according to the time taken by the preliminary investigate, he cleaned some samples those were completed with are obviously too short time (less than 120 seconds) and those with obviously too long time (more than 720 seconds). With the timing statistics function on the Questionnaire Star platform, a total of 18 questionnaires with short and long answering time were pinpointed and excluded. Then with manual investigation, it was determined that 15 samples were not filled with high quality and were considered invalid questionnaires to be deleted. Subsequently, in order to further ensure the validity of the data of other questionnaires, through manual identification, 45 questionnaires without discrepancy in answering (options are all consistent or homogeneous) were removed from the remaining 714 questionnaires. Finally, after data cleaning, 669 valid data samples for empirical analysis were obtained from 729 respondents, and the sample valid rate of the questionnaire was 91.77%.

4.6 Chapter summary

This chapter is the fourth part of the thesis, which mainly includes the establishment of research models, research hypotheses, questionnaire design, scale development, preliminary investigation, data collection and rearrangement.

(1) Based on the literature research and the determination of variables, this study built the “hypotheses model of factors influencing users’ PI” based on PV, PR and TAM, as shown in Figure 4-2. “purchase intention” is the dependent variable of the research model to reflect the user’s willingness to purchase the course. PV, TSA, CFT, PU, PEU, PR, PC and WM are 8 explanatory variables that potentially affect user’s willingness to purchase the course. In addition, according to the characteristics of the Chinese B2B2C OEP, this study selected age, education and income level as control variables to study their impacts on the user’s willingness to purchase the course.

(2) Based on previous research results, the Chinese B2B2C OEP is used as the research scenario to study the relevant factors affecting the user’s PI on B2B2C OEP in China, and the impacts of various factors influencing PV. At the same time, this study also proposed that PV is used as a mediator, and the hypothesis that WM plays a moderator role between PV and PI. In order to better verify the scientific nature of the research model, a total of 16 research hypotheses were proposed in this study, as shown in Table 4-2.

(3) In the process of this study, he developed the principles for the preparation of the questionnaire and determined the content, structure and procedures of the questionnaire.

(4) In terms of variable measurement, this study has designed and developed a scale for measuring latent variables with the reference to domestic and international maturity scales and under the special circumstances of B2B2C OEP.

(5) The questionnaire was designed using the Linkert 7-point scale. Extreme disagreement to extreme agreement is represented by 1 and 7 respectively, based on which the preliminary investigation of this study was formed. Through this preliminary investigation, 63 valid questionnaires were received. Based on the reliability and validity analysis, the questionnaires

were adjusted and optimized according to the feedback, and the formal questionnaire of this study was finally formed.

(6) According to the requirements of using SEM to test hypothesis, the sample capacity required for this study was determined. This study used the Questionnaire Star as the carrier of the final platform to issue questionnaires that was later sent to the users of OEPs by means of QQ learning groups of the DC Academy, Himalayan FM, Maimai APP. A total of 997 questionnaires were collected during the survey, and 669 valid data samples for empirical analysis were obtained through data cleaning and deletion of invalid questionnaires.

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Chapter 5: Data Statistics and Analysis

5.1 Data analysis methods and tools

Structural Equation Modeling (SEM), a method based on linear statistical modeling technology was proposed by Joreskog (1970). In recent years, SEM has been greatly developed, and many empirical researches in the humanities and social sciences have adopted this modeling method. This method can be used for related studies of latent variables. Usually, latent variables refer to ones that cannot be accurately measured. In order to measure latent variables, some observable variables are used as “indicators” to indirectly measure the latent variables. The SEM is a multivariate statistical method to measure the relationship between observable and latent variables, and the relationship between latent variable and latent variable. Partial Least Squares (PLS) analysis was first proposed by Wood and Albano in 1983. Compared with other research methods, PLS has the following advantages that are more conducive to this research:

- PLS requires a relatively small sample size.
- PLS allows non-normally distributed data, which is suitable for the research that collects data by the Likert scale, and this study uses the Likert scale for data collection.
- PLS is suitable relatively complex structural equation models with many constructs. The model of this study contains 9 constructs, so the number of constructs is relatively large, and the model is complex.
- Compared with theoretical tests, PLS is more suitable for the development of theory. The model of this study has been innovatively integrated many theories. Therefore, PLS is more suitable for analysis of this research.
- PLS is more conducive to prediction. This study expects to provide model predictions and references for commercial OEPs, so PLS analysis is more applicable.

Based on the above analysis, this study used the PLS-SEM method for data analysis. IBM SPSS V24.0 was chosen as the data analysis tool and SmartPLS 3.2.8 was selected as the structural equation modeling software.

5.2 Descriptive statistical analysis

5.2.1 Descriptive statistical analysis of demographic characteristics of sample data

The questionnaires obtained in this study were all conducted using online questionnaires. Users were invited to complete the questionnaire via online community of OEP and social software. CINIC (2019) revealed the data about demographic portrait according to the Baidu Index (2019) from July 1, 2013 to May 3, 2019, with the keyword “online education”.

Table 5-1 Demographic information summary of the sample

Variable	Description	Number	Percentage
Name	Male	329	49.2%
	Female	340	50.8%
Age	Below 18 years old	19	2.8%
	19-25 years old	239	35.7%
	26-35 years old	261	39.0%
	36-45 years old	110	16.4%
	Above 46	40	6.0%
Education	Below high school (below technical secondary school)	27	4.0%
	Junior college	113	16.9%

	Bachelor	304	45.4%
Education	Master	175	26.2%
	Doctor	50	7.5%
	Students	201	30.0%
	Staff in private sector	252	37.7%
	Staff in state-owned enterprises	114	17.0%
Job	Civil servants	17	2.5%
	Social organization	3	0.4%
	Business owner and self-employed individual	55	8.2%
	Others	27	4.0%
	Below 30,000 RMB	191	28.6%
	40,000-100,000 RMB	152	22.7%
Annual income	110,000-200,000 RMB	170	25.4%
	210,000-300,000 RMB	73	10.9%
	Above 310,000 RMB	83	12.4%

Table 5-2 Representativeness of the sample

	Entirety (the overall situation of citizens in China)		**Samples**	
Gender	**Unit: million people**	**Percentage**	**Unit: people**	**Percentage**

Male	436.883	52.7%	329	49.2%
Female	392.117	47.3%	340	50.8%
Total	829	100%	669	100%

Note: Figures in the “Entirety” column are from CINIC (2019).

As can be seen from Table 5-1, there were 329 male and 340 female respondents. The proportion of males and females in the total sample was 49.2% and 50.8% respectively. The number of female interviewees was slightly higher than that of male ones, but the proportion of males and females was similar.

The gender structure in CINIC showed that by the end of December 2018, the ratio of men and women Chinese netizens was 52.7 to 47.3. It can be seen that the proportion of males in Chinese netizens was 52.7%, and that of women was 47.3%. It can be concluded from Table 5-2 shows that the ratio of male to female netizens in CINIC is roughly the same as the ratio of male to female respondents in the sample without excessive deviation.

In terms of age, Table 5-1 shows that the majority of the respondents (261 respondents) were 26 to 35 years old, accounting for 39.00% of the total sample; followed by ages 19 to 25 (239 respondents), accounting for 35.70%. It can be concluded that the respondents aged 19-35 accounted for 74.40% of the total respondents. Young people became the main users of the OEP, and this is in line with the fact that young people are active on the Internet.

According to the demographic portraits of Baidu Index (2019) from July 1, 2013 to May 3, in 2019 with the keyword “online education”, the proportion of people aged 20 to 29 was 17%, the proportion of people aged 30 to 39 was 57%, the proportion of people aged 40-49 was 18%, and the proportion of users aged 20-49 was 90%, which is consistent with the fact that the majority of the subjects in this study ages 19 to 45. Most of the respondents in this study were between 19 to 45 years old, which is consistent with the figure that the age of 65.9% Internet users was 20 to 49 according to CINIC (2019). The age characteristics of the respondents in this study align with the argumentation in CINIC (2019) that “the age structure of Chinese netizens is mainly youth and middle-age, and there are signs of continuous penetration into middle-aged and high-aged population".

It can be seen from Table 5-1 that in the study, as for education background, the maximum number is undergraduate students (304 respondents), accounting for 45.40% of the total respondents, and the lowest number (27 respondents) is high school (secondary school) and below, accounting for 4.00% of the total sample. There are 113 college students, accounting for 16.90% of the total respondents; 175 graduate students, accounting for 25.20%. among highly educated respondents, the number of those with doctoral degree is 50, accounting for 7.5% of the total respondents.

It can be seen that the proportion of users with advanced degrees in all OEP users is relatively high. This is due to the way that all the surveys were conducted using online questionnaires. Most of the respondents were students, employees in enterprises and institutions. These groups use computers and mobile Internet devices more frequently, and the quality of questionnaires completed by them is relatively high thanks to their better understanding. In summary, the distribution of respondents' education background is consistent with the using scenario of OEPs, so the results have certain rationality.

As can be seen from Table 5-1, in terms of occupation, the largest proportion is employees in enterprises, and the number is 252, accounting for 37.70% of the total respondents. The number of students is 201, accounting for 30.00% of the total respondents. There are 114 respondents who work in the public institutions, accounting for 17.00% of the total respondents. The competency and quality of staffs in private and public sectors, as well as students are relatively high. They are also relatively familiar with the survey of online questionnaires, so the online questionnaires filled by them demonstrate relatively high quality. From the aspect of occupational distribution, the respondents have covered a wider range of occupations and reasonably distributed.

As can be seen from Table 5-1, in terms of annual income, the number of respondents with annual income below 30,000 yuan is 191, accounting for 28.60% of the total sample. The number of respondents with annual income from 400,000 to 100,000 yuan is 152, accounting for 22.70% of the total sample. 170 respondents have an annual income from 120,000 to

200,000 yuan, accounting for 25.40% of the total sample. The annual income of the majority of the respondents is under 200,000 yuan, accounting for more than 76% of the total, which is in line with the distribution that the proportion of staffs in enterprises and public institutions, as well as students is relatively high. From the analysis of the annual income distribution, the data obtained in this questionnaire is fairly reasonable, in line with the income structure of users of OEPs.

5.2.2 Descriptive statistical analysis of the use of OEPs

When issuing questionnaire online, this study also collected data on OEP used by the respondents, including which OEPs were used by the respondents, and whether they purchased paid courses on OEP.

Table 5-3 shows that the platform used by the most respondents (360 people) in this study is "NetEase Cloud Classroom (Youdao)", accounting for 53.81% of the total respondents; followed by "others education platforms not listed in the options" that have been used by 204 people, accounting for 30.49% of the total respondents. Tencent Classroom and Hujiang Network School (including CCtalk) rank the 3rd and the 4th, accounting for 29.00% and 24.36% of the total number of respondents respectively.

Table 5-3 Descriptive statistical analysis of OEPs used by respondents

Item	Description	Number of observations	Percentage
What OEPs have you used?	NetEase Cloud Classroom (Youdao)	360	53.81%
	Hujiang Network School (including CCtalk)	163	24.36%
	Taobao Education (Taobao University)	118	17.63%
	Tencent Classroom	194	29.00%

	Baidu Chuanke	60	8.97%
	YOUKU Classroom (YOUKU education channel)	46	6.88%
	YY Education	32	4.78%
	Duobei.com	7	1.05%
	Taboke.com	39	5.83%
	Sina open class	100	14.95%
	Others	204	30.49%
Have you ever bought any paid courses on OEP?	Not intend to buy.	170	25.41%
	I am choosing.	99	14.80%
	Yes and I am studying now.	228	34.08%
	Yes and I finished learning.	172	25.71%
The content of what you learned.	Certificates	180	26.91%
	Vocational skills	396	59.19%
	Top-up and postgraduate exam courses	59	8.82%
	Civil servant exam training	44	6.58%
	English training	184	27.50%
	Hobbies	341	50.98%
	Others	65	9.72%

By comparison, the number of users of OEPs operated by diversified Internet companies such as NetEase, Tencent, Taobao, and Sina is relatively high, which is inseparable from the large user base in these diversified Internet companies. However, the proportion of choosing "other OEPs not listed in the questionnaire" option also accounts for 30.49% of the total respondents. It indirectly indicates that the number of OEPs in China is enormous, which is in line with the fact that OEPs are surging in China.

As can be seen from Table 5-3, the number of respondents who are not planning to purchase is 170, accounting for 25.41% of the respondents. 99 people are planning to purchase, accounting for 14.80% of the respondents. 228 people have bought courses and are learning, accounting for 34.08%. 172 once bought online courses and completed their learning, accounting for 25.71% of the respondents. It can be seen that the users with experience in buying courses on OEP consist of those already have bought courses and are learning as well as those who once bought online courses and completed their learning. users with experiences in buying courses on OEP consist of those do not intend to buy and those who are selecting courses to buy.

According to the situation of "the content of what you learned" in Table 5-3, the number of respondents who account for the highest proportion is "vocational skills", at 396, accounting for 59.19% of the total number. The second largest proportion is for hobbies and personal interest, which number is 341, accounting for 50.98% of the total number. The third largest proportion is for English training and certificates, which total 184 and 180 respectively, accounting for 27.50% and 26.91% respectively. As can be seen from Table 5-3, courses related to vocational skills and hobbies are most popular courses among users, while English training and certificate acquisition enjoy similar level of popularity, only next to vocational skills and hobbies.

5.2.3 Descriptive statistical analysis of variables in the model

In this study, the minimum, maximum, average, skewness, kurtosis and standard deviation of each variable and specific item were calculated by the analysis software, IBM SPSS 24.0. The calculation results are shown in Table 5-4.

Table 5-4 descriptive statistics of variable measure items

Variable	**Item**	**N**	**Mini**	**Max**	**Avg**	**SD**	**Skewness**	**Kurtosis**
TSA	TSA1	669	1	7	5.492	1.308	-0.783	0.326
	TSA2	669	1	7	5.501	1.297	-0.745	0.326
	TSA3	669	1	7	5.658	1.264	-0.867	0.415
	TSA4	669	1	7	5.716	1.269	-0.931	0.475
CFT	CFT1	669	1	7	5.649	1.324	-0.920	0.370
	CFT2	669	1	7	5.713	1.301	-1.195	1.535
	CFT3	669	1	7	5.701	1.255	-0.971	0.725
	CFT4	669	1	7	5.511	1.322	-0.843	0.481
PU	PU1	669	1	7	4.994	1.362	-0.524	0.109
	PU2	669	1	7	4.934	1.324	-0.422	-0.106
	PU3	669	1	7	5.260	1.286	-0.663	0.338
	PU4	669	1	7	4.934	1.335	-0.424	-0.025
PEU	PEU1	669	1	7	4.822	1.390	-0.344	-0.202
	PEU2	669	1	7	5.070	1.319	-0.495	0.013
	PEU3	669	1	7	4.451	1.479	-0.256	-0.459
	PEU4	669	1	7	4.857	1.378	-0.388	-0.170
PR	PR1	669	1	7	5.326	1.491	-0.779	0.067

	PR2	669	1	7	5.294	1.447	-0.707	0.005
	PR3	669	1	7	5.202	1.597	-0.748	-0.093
	PR4	669	1	7	5.112	1.528	-0.674	-0.075
PC	PC1	669	1	7	4.719	1.437	-0.359	-0.074
	PC2	669	1	7	4.398	1.508	-0.175	-0.337
	PC3	669	1	7	4.274	1.528	-0.149	-0.572
	PC4	669	1	7	4.344	1.609	-0.217	-0.611
PV	PV1	669	1	7	5.076	1.446	-0.661	0.150
	PV2	669	1	7	5.123	1.464	-0.652	-0.023
	PV3	669	1	7	5.138	1.432	-0.749	0.301
	PV4	669	1	7	5.139	1.424	-0.740	0.430
WM	WM1	669	1	7	5.381	1.483	-0.847	0.205
	WM2	669	1	7	4.688	1.329	-0.242	-0.153
	WM3	669	1	7	4.710	1.322	-0.274	-0.121
	WM4	669	1	7	4.641	1.305	-0.254	-0.060
PI	PI1	669	1	7	5.350	1.505	-0.977	0.619
	PI2	669	1	7	5.184	1.475	-0.733	0.250
	PI3	669	1	7	5.572	1.397	-1.025	0.710
	PI4	669	1	7	5.432	1.438	-0.882	0.435

effective N (status list)：669

As can be seen from Table 5-4, the variables included in the model of this study are PV, WM, PR, PC, PU, PEU, CFT, TSA, and PI. The number of items for each variable is 4, which meets the requirements of statistical analysis of IBM SPSS.

As shown in Table 5-4, the absolute value of the kurtosis of all the items is less than 8 and the absolute value of the skewness of all the items is less than 3. The results indicate that the sample data obtained in this study have met the requirements of normal distribution (Chen, 2017), and they are also suitable for the subsequent data analysis by SEM used in this study.

Table 5-5 Descriptive statistics of variables

Variables	**N**	**Average**	**SD**
TSA	669	5.592	1.115
CFT	669	5.643	1.062
PU	669	5.031	1.132
PEU	669	4.800	1.166
PR	669	5.234	1.266
PC	669	4.433	1.255
PV	669	5.119	1.180
WM	669	4.855	1.176
PI	669	5.385	1.236

effective N (status list)：66

As can be seen from Table 5-4 and Table 5-5, the average value of the PV variables is

5.119, and the standard deviation is 1.180. The item PV4 that is “I think that buying online course is valuable and meaningful” has the highest average value, at 5.139. The item PV3 that is “I think that buying online course is worthy compared with what I have paid out” has the second highest average value. The average value of the other items is all at 5.0 or above, indicating that users of OEPs generally believe that the value of online courses is relatively high, and they are perceived as online education products containing relatively high value.

The average value of the WM variables is 4.855 and the standard deviation is 1.176. The items WM1 that is “before purchasing online courses, I will refer to the relevant comments of the course” has the highest average value, at 5.381. The average of the remaining items is lower than 4.8, indicating that users of OEPs generally do not score WM very high.

The average value of the PR variables is 5.234 with a standard deviation at 1.266. The item PR1 that is “I will worry that the quality of the course will not meet my expectation when I bought online courses” has the highest average, at 5.326. The item PR4 that is “I will worry that guarantee of after-sales service cannot be ensured when I bought online courses” has the smallest average, at 5.112. The average of other items is also over 5. The above figures show that users of OEPs are worried that online courses cannot achieve the expected quality, which is also an important factor restricting users on OEP from buying online courses.

The average of PC variables is 4.433 with a standard deviation at 1.255. The item PC1 that is “I think the online course price is relatively high” has the highest average, at 4.719. The item PC3 that is “online course does not shorten my time and energy needed to grasp knowledge” has the lowest average, at 4.274. The average of other items also exceeds 4. Overall, users on OEP believe that the price of online courses is relatively high, which undermines users’ willingness to purchase online courses.

The average of PU variable is 5.031 with a standard deviation at 1.132. The item PU3 that is “I think the online course can help me get more knowledge” has the highest average, at 5.260. The item PU2 that is “I think the online course can improve my learning effect” and the item PU4 that is “I think online courses make my learning easier” have the lowest average, at 4.934. It can be explained from these figures that users of OEP generally believe that online courses can help access to more extensive knowledge.

The average of PE variables is 4.800 with a standard deviation at 1.166. The item PEU2 that is “I can easily use the OEP for course learning” has the highest average, at 5.070 while the item PEU3 that is “I can easily contact the online course suppliers” has the lowest average, at 4.451. It can be explained that users of OEPs believe that it is easy to use the system provided by the platform to learn online courses.

The average of CFT variables is 5.643 and the standard deviation is 1.062. The item of CFT2 that is “If the CFT meet my expectation, my willingness to buy will increase” has the highest average, at 5.713. The item CFT4 that is “If the online course provides CFT will affect my willingness to buy” has the lowest average, at 5.511. The averages of other items also exceed 5.5. These figures indicate that users of OEPs believe that the CFT can increase consumers’ purchase willingness, and if CFT can live up to consumers’ exception, their purchase willingness will be enhanced.

The average of TSA variables is 5.592 and the standard deviation is 1.115. The item TSA4 that is “I can decide where and when to study online” has the highest average, at 5.716, and the item TSA1 that is “I can decide the learning content when I am studying online” has the lowest average, at 5.492. The other items have averages over 5.4. The above-mentioned figures indicate that users of OEPs generally believe that TSA has key impacts on their own learning online.

The average of PI variables is 5.385 with the standard deviation at 1.236. The item PI3 that is “If the online course is what I need, I am willing to buy it” has the highest average, at 5.572, and the item PI2 that is “I will continue to purchase the paid course of the OEP” has the lowest average, at 5.184. The average of the rest measurement items also exceeds 5.1, which explains that users of OEP are still very willing to purchase online courses.

According to average value, the average value of each item is between 4.274 and 5.716. From the results, it can be concluded that responses to items generally show a positive attitude and orientation. According to standard deviation, the standard deviation of all items is between 1.255-1.609, which indicates that the score of the items done by respondents does not fluctuate greatly, and the overall distribution of the data is reasonable.

5.3 Reliability validity and data test

5.3.1 Reliability and validity analysis of questionnaire data

(1) Reliability analysis of questionnaire data

Reliability is used to measure the credibility or stability within a scale. The α coefficient proposed by Cronbach in 1951 has been used to measure the consistency of each item. The higher α value means better consistency of each item in the questionnaire, indicating that the reliability of the questionnaire is higher (Meng, 2013; Liu, 2016; Hou, 2018). Statistical analysis of the reliability of the nine variables that are PV, WM, PR, CFT, PEU, TSA, PU, PI, and PC were performed by IBM SPSS software, and its results can be seen in Table 5-6.

Table 5-6 Summary of Cronbach's alpha of variables

Variable	Number of items	Cronbach's alpha
CFT	4	0.834
PC	4	0.844
PEU	4	0.859
PI	4	0.871
PR	4	0.855
PU	4	0.876
PV	4	0.836
TSA	4	0.891
WM	4	0.886

Internal consistency: 36	0.861

When the Cronbach's alpha coefficient is greater than 0.7, it indicates the internal consistency of the questionnaire is credible. From Table 5-6, it can be learned that the overall alpha value of the questionnaire is 0.861, which indicates that the questionnaire has a high reliability. The alpha value of the remaining 9 variables is all greater than 0.8, indicating that each variable has good reliability. It can be concluded that the questionnaire as a whole has good reliability.

(2) Validity analysis of questionnaire data

Under the condition that the reliability of the questionnaire has reached the standard, in order to ensure that questions in the questionnaire can honestly and effectively reflect the meaning of the research variables, its validity was analyzed. The "factor analysis" function in the IBM SPSS analysis software has been used to access Kaiser-Meyer-Olkin (KMO) and the Bartlett sphericity test has been performed. If KMO is greater than 0.8, the validity is very high (Fang, 2016).

Table 5-7 KMO and Bartlett sphericity test

The number of KMO sample applicableness		0.917
Bartlett sphericity	approximate chi-square	12988.833
	degree of freedom	630
	significance	0.000

As can be seen from Table 5-7, the KMO value of the questionnaire in this study is 0.917, indicating that the validity is very high. The approximate chi-square of the Bartlett sphericity test is 12988.833, and the significance is 0.000<0.001, indicating that the questionnaire is very significant, so the data structure of the questionnaire has very good validity (Meng, 2013; Liu, 2017).

5.3.2 Reliability and validity analysis of the model

This study has combined PLS Algorithm and Bootstrapping of SmartPLS to calculate the combined reliability, internal consistency coefficient, convergence validity and discriminant validity of the measurement model. The number of samples in Bootstrapping is set as 669.

Table 5-8 Factor load and cross factor load table

	CFT	PC	PEU	PI	PR	PU	PV	TSA	WM
CFT1	**0.815**	-0.109	0.191	0.244	-0.179	0.195	0.199	0.208	0.286
CFT2	**0.813**	-0.081	0.239	0.270	-0.215	0.240	0.234	0.234	0.241
CFT3	**0.834**	-0.145	0.206	0.259	-0.209	0.214	0.222	0.186	0.304
CFT4	**0.805**	-0.052	0.244	0.263	-0.189	0.209	0.191	0.200	0.257
PC1	-0.110	**0.826**	-0.126	-0.195	0.148	-0.154	-0.342	-0.141	-0.101
PC2	-0.108	**0.798**	-0.110	-0.152	0.118	-0.136	-0.267	-0.085	-0.097
PC3	-0.094	**0.842**	-0.117	-0.186	0.138	-0.143	-0.334	-0.146	-0.082
PC4	-0.081	**0.831**	-0.098	-0.188	0.184	-0.123	-0.311	-0.082	-0.122
PEU1	0.203	-0.110	**0.824**	0.278	-0.236	0.300	0.309	0.271	0.239
PEU2	0.216	-0.081	**0.855**	0.300	-0.259	0.276	0.314	0.244	0.191
PEU3	0.236	-0.136	**0.832**	0.272	-0.248	0.289	0.330	0.210	0.204
PEU4	0.247	-0.129	**0.840**	0.333	-0.276	0.304	0.362	0.291	0.186
PI1	0.278	-0.202	0.290	**0.856**	-0.345	0.316	0.491	0.457	0.372

PI2	0.308	-0.202	0.319	**0.890**	-0.388	0.310	0.496	0.464	0.409
PI3	0.236	-0.164	0.296	**0.804**	-0.343	0.278	0.484	0.430	0.307
PI4	0.253	-0.178	0.297	**0.848**	-0.352	0.323	0.451	0.452	0.322
PR1	-0.203	0.164	-0.279	-0.360	**0.836**	-0.257	-0.431	-0.302	-0.218
PR2	-0.206	0.124	-0.233	-0.306	**0.808**	-0.221	-0.383	-0.248	-0.194
PR3	-0.196	0.168	-0.256	-0.382	**0.871**	-0.280	-0.433	-0.257	-0.206
PR4	-0.209	0.138	-0.246	-0.351	**0.823**	-0.273	-0.398	-0.261	-0.181
PU1	0.252	-0.134	0.250	0.300	-0.239	**0.828**	0.426	0.312	0.186
PU2	0.200	-0.127	0.303	0.303	-0.279	**0.838**	0.463	0.287	0.193
PU3	0.243	-0.164	0.300	0.328	-0.295	**0.899**	0.476	0.287	0.211
PU4	0.207	-0.151	0.334	0.301	-0.243	**0.850**	0.447	0.287	0.214
PV1	0.206	-0.318	0.357	0.467	-0.379	0.422	**0.831**	0.361	0.234
PV2	0.237	-0.286	0.324	0.457	-0.409	0.442	**0.823**	0.373	0.273
PV3	0.182	-0.329	0.291	0.462	-0.430	0.393	**0.798**	0.347	0.190
PV4	0.224	-0.319	0.316	0.466	-0.398	0.480	**0.821**	0.359	0.262
TSA1	0.215	-0.153	0.268	0.488	-0.277	0.311	0.425	**0.885**	0.267
TSA2	0.240	-0.146	0.263	0.480	-0.303	0.300	0.386	**0.887**	0.269
TSA3	0.248	-0.098	0.275	0.432	-0.261	0.299	0.353	**0.818**	0.253
TSA4	0.179	-0.084	0.252	0.438	-0.270	0.279	0.359	**0.883**	0.216

WM1	0.303	-0.076	0.225	0.353	-0.222	0.184	0.253	0.248	**0.894**
WM2	0.305	-0.107	0.252	0.406	-0.243	0.236	0.293	0.263	**0.902**
WM3	0.289	-0.138	0.194	0.334	-0.205	0.201	0.244	0.238	**0.862**
WM4	0.249	-0.102	0.166	0.338	-0.152	0.191	0.217	0.251	**0.794**

It can be known from Table 5-8 and Table 5-9 that: (1) The factor load of all factors is greater than 0.5 and the level is relatively high; (2) The composite reliability (CR) of the nine latent variables is greater than or equal to 0.8; (3) Cronbach's alpha coefficient of all latent variables is higher than 0.7; the combined reliability CR value of the latent variable and the minimum Cronbach's alpha coefficient are not less than 0.7, indicating that the measurement model has good internal consistency reliability (Straub, Boudreau, & Gefen, 2004; Luo, 2014; Wang, 2017). Based on the above analysis, the measurement model of this study can be considered to have good reliability.

The validity of the measurement model is usually measured by content validity, convergence validity, and discriminant validity. All measurement items in this study were adapted from the previous research literature, and the pre-investigation before the formal questionnaire survey were conducted to ensure the validity of the content of the scales. Therefore, it is rational to consider that the scales of the research are clear, accurate, and valid in content. has content validity.

The average variance extracted (AVE) is greater than 0.5, which indicates that the variables have ideal convergence validity. Table 5-9 shows that the AVE value of the model is greater than 0.6, further indicating that the measurement model has ideal convergence validity (Zhou, 2014; Shangguan, 2015; Liu, 2016).

Discriminant validity can be tested by comparing the square root of AVEs of the latent variable with the correlation coefficient of other latent variables (Fornell & Larcker, 1981; Zhang, 2012; Zeng, 2013; Yu, 2015). Table 5-10 shows the correlation coefficient of the latent variable and the square root of AVE. In the lower triangular region in the matrix, there has been listed the correlation coefficient between the variables, and the square root of the variable AVE can be seen along the angular bisector. It can be seen that the AVE square root of each latent variable in the measurement model is greater than the correlation coefficient between the latent variable and other latent variables, indicating that the measurement model has good discriminant validity.

Table 5-9 AVE, Communality, CR and Cronbach's alpha of the measurement model

Latent variable	**Number of items**	**Convergence validity**		**Reliability**	
		AVE	**Communality**	**Composite Reliability**	**Cronbach's alpha**
CFT	4	0.667	0.667	0.889	0.834
PC	4	0.680	0.680	0.895	0.844
PEU	4	0.702	0.702	0.904	0.859
PI	4	0.722	0.722	0.912	0.871
PR	4	0.697	0.697	0.902	0.855
PU	4	0.729	0.729	0.915	0.876
PV	4	0.670	0.670	0.890	0.836
TSA	4	0.754	0.754	0.925	0.891
WM	4	0.747	0.747	0.922	0.886

The factor load and cross factor load can be used to test the internality and discriminability of the measurement model. As can be seen from Table 5-10, there is a relatively high correlation coefficient between each measurement variable and its latent variable. The factor load (bold ones) of all the measurement items of the latent variable is much larger than the cross-factor load with other latent variables. It further indicates that the measurement model of this study has good internal consistency and differentiation (Jiang, 2013; Chen, 2015; Liang, 2017).

Table 5-10 Correlation coefficient between latent variables and AVE square root

	CFT	PC	PEU	PI	PR	PU	PV	TSA	WM
CFT	**0.817**								
PC	-0.119	**0.825**							
PEU	0.270	-0.137	**0.838**						
PI	0.317	-0.220	0.354	**0.850**					
PR	-0.243	0.179	-0.304	-0.421	**0.835**				
PU	0.263	-0.169	0.349	0.361	-0.310	**0.854**			
PV	0.260	-0.383	0.393	0.566	-0.493	0.531	**0.818**		
TSA	0.254	-0.140	0.304	0.530	-0.320	0.343	0.440	**0.868**	
WM	0.332	-0.122	0.244	0.416	-0.240	0.236	0.293	0.290	**0.864**

Note: The lower triangular region in the matrix is the correlation coefficient between the variables, and the value on the angular bisector is the square root of the variable AVE

5.3.3 Common method deviation test

The questionnaire in this study were all conducted by a single online survey. The survey data was collected by the self-report study of respondents. The self-inflicted common method biases may seriously plague the results of the research and even mislead final conclusions of this study (Doty & Glick, 1998; Du, Zhao, & Liu, 2003; Zhou & Long, 2004; Zhu & Li, 2019). Based on the previous researches, this study has reduced the impacts caused by common method biases from both program control and statistical control (Podsakoff & Organ, 1986).

(1) Program control

In term of program control, the following four strategies were implemented to reduce the impacts of common method bias.

First, during the questionnaire survey, respondents were informed that results of the survey were only used for academic research rather than any other purposes. Second, the online questionnaire survey was all anonymous. The measurement items in the questionnaire did not involve any sensitive information about personal privacy. Third, all variables in the questionnaire were measured by using multiple measurement items. Fourth, based on the previous in-depth interviews and pre-investigation, the items in scales were optimized, and the expression ambiguity was reduced by modifying some expressions and descriptions into more clear and accurate wording.

(2) Statistical control

The Harman's one-factor test was used for statistical control of common method biases. The Harman's one-factor test has been widely used in questionnaire surveys conducted by self-report scale. For example, respondents may tend to choose the middle option when answering the Likert scale to avoid extreme scores, while the Harman's one-factor test can estimate the common method bias. By using the exploratory factor analysis (EFA) function in the IBM SPSS analysis software, the EFA was performed on all the measurement items in the questionnaire. In the unrotated factor analysis results, if the explained variance of the first factor is less than 40%, it can be considered that the impacts of the common method biases is small (Cui, 2010; Yang, 2017; Deng, Li, & Chen, 2018). A total of 8 factors with eigenvalues greater than 1 were extracted from all the items, and the explained variance of the largest factor was 28.184%. There is not the situation where a certain factor explains the majority of the variance, so it is reasonable to assume that the common method biases imposes significant impacts on results of the research.

5.3.4 Multicollinearity test

When constructing a research model, it is also necessary to check whether there is multicollinearity in the structural model. Hair et al. (2016) considered that when the tolerance in the model is less than 0.20 or the variance inflation factor (VIF) is greater than 5, they indicate a serious collinearity in this model. Through SmartPLS calculation, the VIF of each variable is less than 5, and the VIF satisfy the critical level of collinearity described in Table 5-11 and Table 5-12. Therefore, there is no multi-collinearity problem in this model, and the results estimated in the model are relatively stable.

Table 5-11 Inner VIF Values

	Age	**CFT**	**Edu**	**Inco-me**	**PC**	**PEU**	**PR**	**PU**	**PV**	**TSA**	**WM**	**PV * WM**
PI	1.733	1.191	1.408	1.733	1.191		1.389		1.758	1.333	1.222	1.012
PU						1.000						
PV		1.159			1.056	1.259	1.241	1.291		1.257		

Table 5-12 Outer VIF Values

Item	**VIF**	**Item**	**VIF**	**Item**	**VIF**
CFT1	1.864	PI1	2.197	PV1	1.905
CFT2	1.713	PI2	2.633	PV2	1.832
CFT3	1.917	PI3	1.771	PV3	1.686
CFT4	1.744	PI4	2.210	PV4	1.816
PC1	1.782	PR1	1.930	TSA1	2.586
PC2	1.804	PR2	1.830	TSA2	2.648

PC3	1.951	PR3	2.267	TSA3	1.916
PC4	1.911	PR4	1.889	TSA4	2.716
PEU1	1.898	PU1	2.076	WM1	2.956
PEU2	2.210	PU2	1.993	WM2	2.910
PEU3	1.941	PU3	2.857	WM3	2.426
PEU4	1.933	PU4	2.133	WM4	1.736
income	1.000	PV * WM	1.000	age	1.000
				education	1.000

5.4 Model hypothesis test and analysis

5.4.1 Structural model validation

In this study, SmartPLS was used to construct the model. After the calculation using PLS Algorithm, the model was analyzed to obtain the calculation results of the PLS structural equation model. Based on Sarstedt, Henseler, and Ringle (2011) recommendations for the number of samples, the study used a self-service method to select 5000 samples with resamples to analyze the significance of the path coefficients. The PLS structural equation model for users' PI of courses on OEP is shown in Figure 5-1.

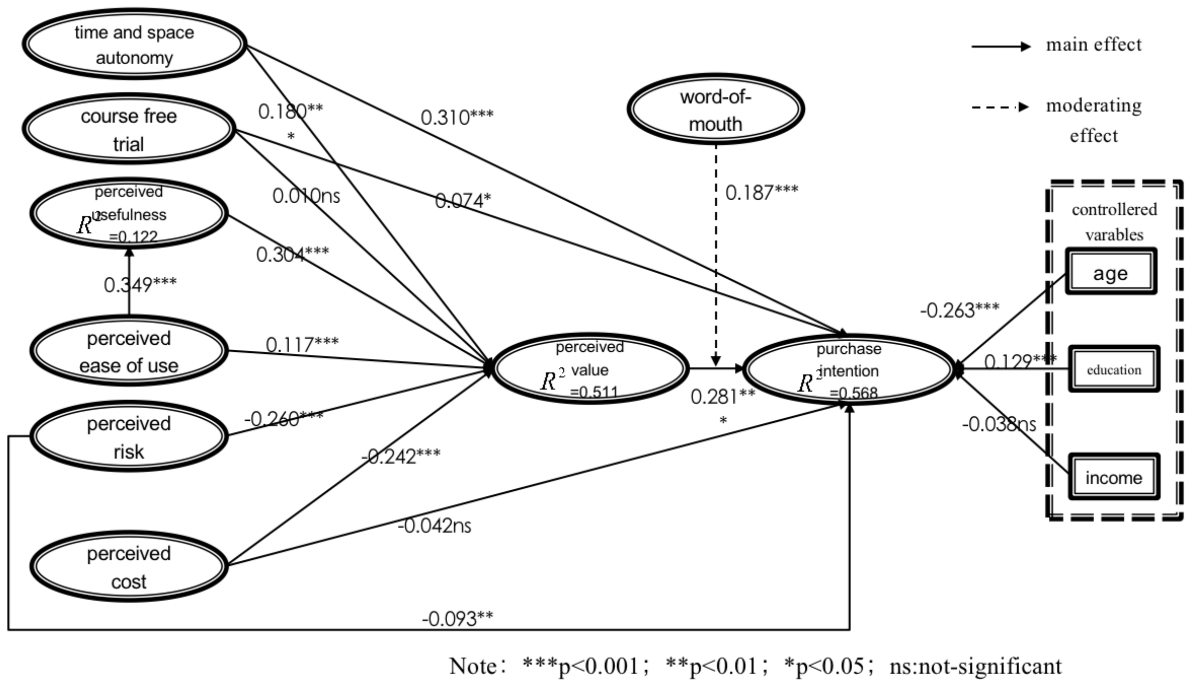

Figure 5-1 PLS structural equation model for OEP users' willingness to purchase courses

When the T value is large than 1.96 in the PLS-SEM model, this indicates that the model has reached a significant level when the α value is 0.05 (shown by *). When the T value is large than 2.58, this indicates that the model has reached a significant level when the α value is 0.01 (shown by **). When the T value is large than 3.29, this indicates that the model has reached a significant level when the α value is 0.001 (shown by ***) (Xie & Zhang, 2014; Zhu & Liao, 2017).

The results of the final calculation of the model show that the T values of CFT→PV and PC→PI are all less than 1.96. The impacts of hypotheses H5 and H11 are not significant, so hypotheses H5 and H11 are not established. As for the control variables, the T value of the path of income to PI does not reach a significant level, indicating that H14c is not supported. As for the rest hypotheses that include H1, H2, H3, H4, H6, H7, H8, H9, H10, H12, H13, H14a, and H14b, hypotheses H1, H2, H4, H6, H7, H8, H9, H12, H13, H14a, and H14b have reached a significant level with alpha value at 0.001, hypothesis H3 has reached a significant level with alpha value at 0.01, and hypothesis H10 has reached a significant level with alpha value at 0.05.

As for the hypothesis H1, the path coefficient of users' PV to PI is 0.281, the T value is

8.073, and the P value is 0.000, which is significant at the 0.010 level. It indicates that the PV of the user has a significant and positive affect on PI of the course, and that greater PV imposes greater impacts on PI of users on online educational platforms.

As for the hypothesis H2, the path coefficient of the WM moderating PV to PI is 0.187, the T value is 6.961, and the P value is 0.000, which is significant at the 0.000 level. It illustrates that WM has significant and positive moderation on the impacts of PV on PI. That the hypothesis H2 is supported indicates that greater PV delivers more stronger PI on OEP under the circumstance of relatively high WM. Meanwhile, the PV and PI have significant and positive impacts.

As for the hypothesis H3, the path coefficient of PR to PI is -0.093, the T value is 3.145, and the P value is 0.002, which is significant at the 0.010 level. It indicates that the PR has a significant and negative impacts on PI, and that greater PR reduces users' PI.

As for the hypothesis H4, the path coefficient of PR to PV is -0.260, the T value is 8.780, and the P value is 0.000, which is significant at the 0.000 level. It indicates that the PR has a negative impact on PV. That the hypothesis H4 is established means that the PR has a significant impact on PV.

As for the hypothesis H5, the path coefficient of users' PC to PI of is -0.042, the T value is 1.523, and the P value is 0.128, which indicates that the significance has not been verified. It means that the hypothesis that PC has a negative impact on PI is invalid. That the hypothesis H5 is not established means that users' PC does not significantly affect their PI.

As for the hypothesis H6, the path coefficient of users' PC to PV is -0.242, the T value is 8.775, and the P value is 0.000, which is significant at the 0.000 level. It means that PC has a negative impact on PV, and it can be concluded that the higher PC reduces users' PV of courses.

As for the hypothesis H7, the path coefficient of users' PU to PV is 0.304, the T value is 9.864, and the P value is 0.000, which is significant at the 0.001 level. It indicates that the PU has a significant and positive impact on PV, and that greater usefulness that users can perceived on OEP, the greater value users will perceive.

As for the hypothesis H8, the path coefficient of users' PEU to PV is 0.17, the T value is 3.658, and the P value is 0.000, which is significant at the 0.001 level. It indicates that the PEU has a significant and positive impact on PV, and that when the PEU is high, users will have considered the courses with higher value.

As for the hypothesis H9, the path coefficient of users' PEU to PU is 0.349. When the path coefficient is greater than 0.2, it indicates that the impacts level is relatively high. T value is 10.135, and P value is 0.000, which means significance at the 0.0001 level. It indicates that the PEU has a significant and positive impact on PU. That the hypothesis H9 is supported illustrates that the higher PEU delivers higher PU to users.

As for the hypothesis H10, the path coefficient of the CFT to PI is 0.074, the T value is 2.522, and the P value is 0.012, which is significant at the 0.05 level. It indicates that the CFT has a significant and positive impact on PI, which means that if OEP provides CFT from which users gain good experiences, they will have stronger PI.

As for the hypothesis H11, the path coefficient of the CFT to PV is 0.010, the T value is 0.335, and the P value is 0.738. The significance is not proved, which indicates that the hypothesis that CFT has a positive impact on PV does not supported. Therefore, it can illustrate that the CFT services and experience provided by OEP do not significantly affect users' PV.

As for the hypothesis H12, the path coefficient of TSA to PI is 0.310, T value is 9.756, and the P value is 0.000, which is significant at the 0.001 level. It indicates that TSA has a significant and positive impact on PI, and it can be concluded that the stronger TSA perceived by users can bring stronger PI.

As for the hypothesis H13, the path coefficient of TSA to PV is 0.180, T value is 5.739, and the P value is 0.000, which is significant at the 0.000 level. It indicates that TSA has a significant and positive impact on PV, and it can be concluded that the stronger TSA delivers more PV.

As for the hypothesis H14a, the path coefficient of users' age to PI is -0.263, the T value is 7.123, and the P value is 0.000, which is significant at the 0.000 level. It illustrates that the user's age has a negative impact on PI, which means that older users are more likely not to buy courses.

As for the hypothesis H14b, the path coefficient of users' educational background to PI is 0.129, the T value is 4.299, and the P value is 0.000, which is significant at the 0.000 level. It illustrates that the user's educational level has significant and positive impacts on PI, which means that users with higher educational level tend to have strong PI.

As for the hypothesis H14c, the path coefficient of income to PI is -0.038, the T value is 1.106, and the P value is 0.269, which indicates that the significance is not proved. It states that the hypothesis that income has a positive impact on PI does not established. the hypothesis H14c is not valid, which means that the user's income level does not have a significant and positive impact on the PI.

5.4.2 Model goodness-of-fitness test

Coefficient of determination (R^2) can measure the accuracy of explanatory relevance and predictive relevance of the model within the framework of the structural equation model. R^2 ranges from 0 to 1, and a higher value indicates a stronger explanatory relevance of each variable in the model to the dependent variable.

Chin (1998) believed that a R^2 greater than 0.333 indicates a level exceeding the average, indicating high explanatory relevance. It can be noted that R^2 of PV is 0.511, R^2 of PI is 0.568, and R^2 of PU is 0.122 from Figure 5-1. The overall explanatory relevance of this model in this study is 0.568, indicating that the model has a good prediction effect (Straub, Boudreau, & Gefen, 2004).

In PLS-SEM, the model's overall indicator can be used to test the Goodness-of-Fitness (GoF) that represents the prediction utility of the entire model. The GoF is calculated as the square root of the product of the average communality and the average R^2. A GoF at 0.36 indicates a good fitness (Wetzels, Odekerken, & Van-Oppen, 2009; Zhou, 2014).

It can be seen from Table 5-9 that the average communality of the measurement model is 0.708 and the average R^2 is 0.401. After calculation, the GoF is 0.533, which indicates a good fitness in the overall model (Hair et al., 2016).

The standardized root means square residual (SRMR) can be used to evaluate GoF. SRMR is defined as the difference between the observed correlation matrix and the predicted correlation matrix of the model to reflect the average magnitude of the difference. When the SRMR value is less than 0.08, the model has a good fitness (Hu & Bentler, 1998; Hair et al., 2016; Cheng, 2017; Cai, Shi, & Chen, 2019).

The SRMR value is 0.035, less than the critical value of 0.08 through SmartPLS operation, which further demonstrates that the overall model of this study has a good fitness and can explain the factors influencing users' willingness to buy courses on OEP.

5.4.3 Model prediction relevance analysis

This study used the Blindfolding function to analyze the predictive relevance of the model, used Cross-validation method of Stone-Geisser's to calculate the predictive relevance of the model, and used Q^2 to evaluate the predictive relevance of the model (Tenenhaus, Vinzi, & Chatelin, 2005; Jiang, 2013). The formula for Q^2 is Q^2 (=1-SSE/SSO). If Q2 is less than 0, it means that the model has no predictive relevance; if Q2 is more than 0, it means that the model has good predictive relevance (Chin, 1998; Zhang, 2012).

Through the calculation of SmarPLS software, the Q^2 of three endogenous variables, PU, PV and PI is 0.383, 0.321 and 0.083 respectively, which are all greater than 0, indicating that the model constructed in this research to study users' course PI on OEP has good predictive relevance.

5.4.4 Mediation effect analysis

The research model of this study introduced a mediation variable of PV, so the mediation effect of PV needs to be analyzed. When selecting a method to test, the literature review on related methods testing mediation effect has been conducted, and through which it can be noted that the most commonly used 4 methods are bootstrapping, product of results approach, distribution of the product strategy and causal steps approach. After comparing these 4 methods and according to Zhao and Han (2007) and Hair et al. (2016), this study finally adopted Bootstrapping to test and analyze the mediation impacts of the mediator.

In the SmartPLS software, the results of the PLS-SEM algorithm and bootstrap functions contain direct impacts, total impacts, and specific indirect impacts. According to the setting recommended by Hair et al. (2016), the number of bootstrap samples was set at 5000, and the confidence interval was set at 95%. The calculation results are shown in Table 5-13.

In the mediation effect analysis, (1) if the indirect effect is not significant, it indicates that there is no mediation effect; (2) if the indirect effect is significant, but the direct effect is not significant, it indicates that the mediation effect is a complete mediation; (3) if the indirect effect and the direct effect are both significant, it indicates that the mediation effect is a partial mediation (Hair et al., 2016; Zhang, 2017).

As can be seen from Table 5-13, the indirect effect of CFT to PI is 0.003 with the confidence interval range from -0.015 to 0.020 which contains 0, so the indirect effect is not significant. The direct effect of CFT to PI is 0.074 with the confidence interval range from 0.015 to 0.129 which does not contain 0, indicating the direct effect is significant. Therefore, PV does not act as a mediation role between CFT and PI.

The indirect effect of PC to PI is -0.068 with the confidence interval range from -0.094 to -0.046 which contains 0, so the indirect effect is significant. The indirect effect of PC to PI is -0.042 with the confidence interval range from -0.094 to 0.012 which contains 0, so the direct effect is not significant. Therefore, PV acts as a complete mediation on the relationship between PC and PI.

Table 5-13 Analysis result of mediation effect

Path	**Effect**	**Initial sample (O)**	**95% confidence intervals**	**T value**	**Significant**	**Type of mediation**
	Direct	0.074	[0.015，0.129]	2.522	Yes	
CFT -> PV -> PI	Total	0.077	[0.014，0.134]	2.511	Yes	No
	Indirect	0.003	[-0.015，0.020]	0.333	No	

	Direct	-0.042	[-0.094，0.012]	1.523	No	
PC -> PV -> PI	Total	-0.110	[-0.163，-0.054]	3.923	Yes	Complete
	Indirect	-0.068	[-0.094，-0.046]	5.672	Yes	
	Direct	-0.093	[-0.153，-0.038]	3.145	Yes	
PR -> PV -> PI	Total	-0.166	[-0.227，-0.111]	5.565	Yes	Partial
	Direct	-0.073	[-0.100，-0.052]	6.118	Yes	
	Direct	0.310	[0.244，0.370]	9.756	Yes	Partial
TSA -> PV -> PI	Total	0.361	[0.300，0.419]	11.842	Yes	Partial
	Direct	0.051	[0.031，0.077]	4.466	Yes	
	Direct	0.117	[0.053，0.178]	3.658	Yes	
PEU -> PU -> PV	Total	0.224	[0.158，0.285]	5.201	Yes	Partial
	Indirect	0.106	[0.079，0.137]	7.182	Yes	

The indirect effect of PR to PI is -0.073 with the confidence interval range from -0.100 to -0.052) which does not contain 0, so the indirect effect is significant. The direct effect of PR to PI is -0.093 with the confidence interval rang from-0.153 to-0.038 which does not contain 0, so the direct effect is significant. Therefore, PV act as a partial mediation on the relationship between PR and PI.

The indirect effect of TSA to PI is 0.051 with the confidence interval range from 0.031 to 0.077) which contains 0, so the indirect effect is significant. The direct effect of TSA to PI is 0.310 with the confidence interval range from 0.244 to 0.370 which does not contain 0, so the direct effect is significant. Therefore, PV act as a partial mediation on the relationship between TSA and PI.

The indirect effect of PEU to PV is 0.106 with the confidence interval range from 0.079 to 0.137) which does not contain 0, so the indirect effect is significant. The direct effect of PEU to PV is 0.117 with the confidence interval range from 0.053 to 0.178 which does not contain 0, so the direct effect is significant. Therefore, PV act as a partial mediation on the relationship between PEU and PV.

In summary, perceived profit (TSA, PEU, PU) and perceived loss (PC, PR) affect the user's PI through the mediator PV, in line with previous research results about PV (Zeithaml, 1988; Butz, 1996; Parasuraman & Grewal, 2000; Zhao, 2013; Fang, Lu, & Liu, 2018).

5.4.5 Moderation effect test

This study also used the SmartPLS analysis software to test the moderation effect. A model in which WM moderates the impacts of PV on PI was established in SmartPLS into which questionnaire data were imported later. The PLS algorithm and bootstrapping functions were used for hierarchical regressions (Al-Gahtani, Hubona, & Wang, 2007; Zhou, 2014; Zhang, 2018), and the results of moderation effect are shown in Table 5-14.

As shown in Table 5-14, the path coefficient β of moderation effect item (PV*WM) and PI is 0.187, indicating that PV*WM has a positive effect on PI. When WM is used as a reference point, the relationship between PV and PI is 0.281. However, when WM increases, the relationship between PV and PI will change with the moderation impacts to 0.468 (0.281 + 0.187), which shows that when WM is high, the explanatory relevance of PV will be strengthened.

The above-mentioned conclusions must be established on the premise that the moderation effect is significant. The calculation results in Table 5-14 show that the path coefficient β of PV and PI is 0.281 with T-value at 8.703, and the path coefficient β of WM and PI is 0.186 with T-value at 6.044. The path coefficient β of the moderation effect item (WM*PV) and PI is 0.187 with T-value at 6.961. All T-values are greater than 1.96, certifying the significance. Therefore, WM imposes a significant positive moderating effect on PV and PI.

Table 5-14 Test result of moderation effect

Hypothesis path	Without Moderator			With Moderator			Hypothesis test result
	Path coefficient β	T-value	Significance	Path coefficient β	T-value	Significance	
PV->PI	0.288	7.899	***	0.281	8.703	***	Hypothesis is supported.
WM->PI				0.186	6.044	***	
PV*WM->PI				0.187	6.961	***	
R^2		0.509			0.568		
f^2					0.066		

Note: ***p<0.001；**p<0.01；*p<0.05；ns: not significant

After adding the moderator of WM, R^2 increased from 0.509 to 0.568, indicating that the PI is affected by the moderator of WM (Lin, 2018). Effect size (f^2) can be used to explain the impacts of exogenous variables on endogenous variables. $0.02<f^2<0.15$ is a weak impact, $0.15<f^2<0.35$ is a moderate impact, and $0.35<f^2$ is a strong impact (Jiang, 2013; Hair et al., 2016). It can be seen from the table that the f^2 of the moderation effect is 0.066, indicating that WM has a weak moderation effect on the relationship between PV and PI.

5.4.6 Analysis of impacts of control variables

By running the SmartPLS software to obtain the standardized path coefficient β and T-value to confirm whether the three control variables, education, age and income, have a significant impact on the model (Li, 2015; Li, 2018).

From Table 5-15, it is a confirmed hypothesis that the user's age (β=0.129, T=4.299, p<0.001) has a negative impact on PI and it is significant. It is a confirmed hypothesis that the user's education background (β=0.073, T=7.123, p<0.001) positively affects PI and it is significant. The hypothesis that the user's income level has a positive impact on PI is not supported.

Table 5-15 Control variable impact analysis

Path	T-value	Significance	Hypothesis test result
education->PI	4.299	***	**Support**
age->PI	7.123	***	**Support**
income->PI	1.106	ns	**Not support**

5.4.7 Analysis of moderated mediation effect

To further explore whether WM can moderate the mediation effect of PV to PI, the model 14 in the Process tool of SPSS were used to test moderated mediation effect. The number of Bootstrap samples is 5000 (Rodríguez, Roldán, & Ariza-Montes, 2014; Wen & Ye, 2014; Fang, Zhao, & Gu, 2014; Chen, 2015; Hayes, 2019), and the results of the calculation are shown in Table 5-16.

From Table 5-16, it can be noted that that path of TSA-PV-PI with WM as the moderator, it has the index of moderated mediation and the 95% confidence interval of mediator index is from 0.032 to 0.067, without 0. It indicates that there is a significant difference in the mediation effect of PI when the WM is at different levels. When WM is in low score group, the mediation effect is 0.041, and the 95% confidence interval is from 0.015 to 0.072 which does not contain 0, indicating that the mediation effect is significant. When WM is in high score group, the mediation effect is 0.156, and the 95% confidence interval is from 0.112 to 0.205, which does not contain 0, indicating that the mediation effect is significant. The mediation 0.156 in high score group is higher than the mediation 0.041 in the low score group, thus indicating that the mediation is positively moderated.

Table 5-16 Moderated mediation effect test

Mediation Path	Moderator	Group (score)	Effect	Boot SE	Bias Corrected (95%)		Index of moderated mediation		
					LLCI	ULCI	Index	LLCI	ULCI
TSA-PV-PI	WM	Low	0.041	0.015	0.015	0.072	0.049	0.032	0.067
		High	0.156	0.023	0.112	0.205			
CFT-PV-PI	WM	Low	0.012	0.007	0.001	0.027	0.014	0.001	0.027
		High	0.044	0.020	0.005	0.084			
PC-PV-PI	WM	Low	-0.036	0.013	-0.063	-0.013	-0.043	-0.059	-0.028
		High	-0.137	0.020	-0.178	-0.100			
PR-PV-PI	WM	Low	-0.044	0.016	-0.077	-0.016	-0.053	-0.071	-0.036
		High	-0.169	0.021	-0.212	-0.129			

Note: ULCI is the upper limit of the confidence interval and LLCI is the lower confidence interval.

That path of CFT-PV-PI with WM as the moderator, it has the index of moderated mediation and the 95% confidence interval of mediator index is from 0.001 to 0.027, without 0. It indicates that there is a significant difference in the mediation effect of PV when the WM is at different levels. When WM is in low score group, the mediation effect is 0.012, and the 95% confidence interval is from 0.001 to 0.027 which dose not contain 0, indicating that the mediation effect is significant. When WM is in high score group, the mediation effect is 0.044, and the 95% confidence interval is from 0.005 to 0.084 which does not contain 0, indicating that the mediation effect is significant. The mediation 0.044 in high score group is higher than the mediation 0.012 in the low score group, thus indicating that the mediation is positively moderated.

The path of PC-PV-PI with WM as the moderator, it has the index of moderated mediation and the 95% confidence interval of mediator index is from -0.059 to -0.028, without 0. It indicates that there is a significant difference in the mediating impacts of PV when the course reputation is at different levels. When WM is in low score group, the mediation effect is -0.036, and the 95% confidence interval is from -0.063 to -0.013 which dose not contain 0, indicating that the mediation effect is significant. When WM is in high score group, the mediation effect is -0.137, and the 95% confidence interval is from -0.178 to -0.100 which done not contain 0, indicating a significant mediating effect. The mediation -0.137 in the high score group is lower than the mediation -0.036 in the low score group, thus indicating that the mediation is negatively moderated.

The path of PR-PV-PI with WM as the moderator, it has the index of moderated mediation and the 95% confidence interval of mediator index is from -0.071 to -0.036, without 0. It indicates that there is a significant difference in the mediation effect of PV when the WM is at different levels. When WM is in low score group, the mediation effect is -0.044, and the 95% confidence interval is from -0.077 to -0.016 which does not contain 0, indicating that the mediation effect is significant. When WM is in high score group, the mediation effect is - 0.169, and the 95% confidence interval is from -0.212 to -0.129 which does not contain 0, indicating a significant mediation effect. However, the mediation -0.044 in low score group is higher than the mediation -0.169 of high score group, thus indicating that the mediation is negatively moderated.

5.5 Multi-group analysis

This study used Multi-Group Analysis (MGA) in PLS-SEM to test whether users who once bought online courses and those never bought online courses are affected by same factors when they make decisions on buying online courses (Wolfgang, Andreas, & Lars, 2010; Sarstedt, Henseler, & Ringle, 2011). The results obtained by running the MGA function of the SmartPLS software are shown in Table 5-17.

Table 5-17 shows that the CFT ($\beta=0.205$, $p<0.001$) significantly affects PI of users who do not have experience in buying online courses, but CFT does not significantly affects PI of users who have experience in buying online courses ($\beta=0.007$, $p>0.8$). This can illustrate that

CFT can impose major impacts on PI of whom never bought courses on OEP before.

Table 5-17 PLS-MGA results

	path coefficient		**T value**		**significant**	
	bought	**not purchased**	**bought**	**not purchased**	**bought**	**not purchased**
AGE -> PI	-0.325	-0.173	7.275	3.075	***	**
CFT -> PI	0.007	0.205	0.174	4.809	ns	***
CFT -> PV	0.018	0.003	0.424	0.069	ns	ns
EDUCATION -> PI	0.065	0.189	1.670	3.967	ns	***
INCOME -> PI	-0.021	-0.034	0.486	0.683	ns	ns
PC -> PI	-0.036	-0.023	1.032	0.474	ns	ns
PC -> PV	-0.314	-0.204	8.611	4.584	***	***
PEU -> PU	0.183	0.544	3.768	12.035	***	***
PEU -> PV	0.018	0.270	0.450	5.563	ns	***
PR -> PI	-0.052	-0.184	1.469	3.472	ns	***
PR -> PV	-0.172	-0.328	4.180	8.194	***	***
PU -> PV	0.267	0.295	7.057	5.340	***	***
PV -> PI	0.262	0.274	6.340	4.405	***	***

TSA -> PI	0.389	0.197	10.624	3.901	***	***
TSA -> PV	0.248	0.035	6.197	0.748	***	ns
WM -> PI	0.187	0.179	4.805	3.721	***	***
moderation -> PI	0.210	0.155	6.879	3.418	***	***

Note: ***p<0.001；**p<0.01；*p<0.05；ns: not significant

The CFT has no significant impacts on the PV of users who have experience in purchasing courses on OEP.

PI of both users who once bought online courses and who never bought online courses are not significantly affected by PC.

The PC owned by users who have experience in purchasing online courses (β=-0.314, $p<0.001$) has a significant impact on PV. The PC owned by users who has never bought any online courses (β=-0.204, $p<0.001$) also significantly affects PV.

Among users who never bought courses on OEP, PEU ($\beta = 0.544$, $p < 0.000$) significantly affects PU, and PEU ($\beta = 0.270$, $p < 0.000$) significantly affects PV. For users who have bought courses on OEP, PEU (β=0.183, $p<0.000$) significantly affects PU, and PEU (β=0.018, $p>0.6$) does not significantly affects PV. Therefore, users who have no experience in purchasing online courses are more likely to think highly of the usability of online courses than those who have bought online courses once.

Among users who have bought courses on OEP once, their PR (β=-0.052, $p>0.1$) does not significantly affect their PI, and their PR (β=-0.172, $p<0.000$) significantly affects their PV. Among the users who never bought online courses before, the PR (β=-0.184, $p<0.000$) significantly affects their PI, and their PR (β=-0.328, $p<0.000$) significantly affects their PV.

The PU (β=0.267, $p<0.000$) of users who have bought courses on OEP once significantly affects PV, and the PU (β=0.295, $p<0.000$) of users without experiences in buying online courses also significantly affects their PV.

On the path of PV ->PI, the PV of the two groups of users who are with and without experience in buying online courses has a significant impact on PI.

The TSA ($\beta = 0.389$, $p < 0.000$) of users of users who have bought courses on OEP significantly affects their PI, and the TSA ($\beta = 0.197$, $p < 0.000$) of users who have never bought courses on OEP before also significantly affects their PI. The TSA T-value of users with online courses purchasing experience is significantly larger than that of users without online courses purchasing experience, indicating that users with purchasing experience are imposed by greater impacts of TSA.

The TSA ($\beta=0.248$, $p<0.000$)of users who have bought courses on OEP significantly affects their PV, but the PV of users without online courses purchasing experience is not significantly affected by TSA ($\beta=0.035$, $p>0.4$) .

The WM ($\beta=0.187$, $p<0.000$) of users who once purchased online courses significantly affects their PI, and the WM ($\beta=0.179$, $p<0.000$) of users who never bought online courses also significantly affects the PV. However, in the case when users have experience in buying online courses, WM positively and significantly affects the PI, and for users without related experience, WM also positively and significantly affect the PI. The two groups of users have significant impacts in the same direction.

Among the three control variables of age, education, and income, age showed significant impacts on PI of no matter whether users have experiences in buying course before. However, the control variable of education has different results in groups with different purchasing experience. As for the group without experience in buying online courses, their education background ($\beta=0.189$, $p<0.001$) significantly affects their PI, but as for the group with experience in buying online courses, their PI is not significantly affected by education background ($\beta=0.065$, $p>0.09$). The control variables of the income of the two groups are not significantly affect their PI.

The moderator MW exerts same impacts in groups of users with different buying experiences. The WM ($\beta=0.210$, $p<0.001$) exerts a significant positive moderation effect on PV and PI in the group of users who once bought online courses, but does not exert the course reputation of users who purchase experience (β=-0.155, $p<0.001$) It has a significant positive moderating effect on PV and PI.

5.6 Chapter summary

This chapter presented statistics and analysis on the data that were collected to explore the factors influencing the users' PI in buying courses on OEP, and the path between various factor variables. This chapter contains five parts: data analysis methods and tool selection, descriptive statistical analysis, reliability and validity analysis, model hypothesis testing analysis, and multi-group analysis.

In order to test the theoretical model proposed in this study, IBM SPSS V24.0 and SmartPLS 3.2.8 were selected for data analysis. A descriptive statistical analysis of 669 questionnaires from the Internet was conducted to describe the basics of the sample, after which reliability and validity analysis proved that the sample data of this study has good reliability and validity, and there was no common method bias or multicollinearity in this data. The model hypothesis test showed that the model has a good fitness, and 13 out of the 16 hypotheses proposed in this study passed the hypothesis test.

Our results show that PV, TSA, CFT, and PR are the key factors directly affecting PI. At the same time, TSA, PU, PEU, PC, PR also affect PI indirectly through affect PV, but the hypothesis that that CFT indirectly affects PI through PV was not confirmed. Age and education in the control variables also directly affect PI, but income does not significantly affect PI (hypothesis failing the test). The study also found that WM has a significant and positive moderation effect on PV and PI. Therefore, it is rational to believe that WM is also one of the factors that are critical to PI in online courses.

In addition, this study also carried out a deeper analysis of multiple groups. In the user group with purchasing experience, TSA is the key factor of PV and it passed the hypothesis test, but this hypothesis was not supported in user group without purchasing experience. On the contrary, in the user group without purchasing experience, CFT, PR, and education have significant impacts PI and passed the hypothesis test, and PU also has significant impacts on

PV. These 4 hypotheses are not valid in the user group with purchasing experience.

Chapter 6: Conclusions and Prospects

6.1 Research conclusions and management implications

By running SmartPLS 3.2.8, the PLS-SEM estimates the impacts of PI of OEP usage, identifying the factors that directly affect PI are TSA, CFT, PR and PV. These four potential variables have different impacts on the dependent variable, PI, and all have passed the significance test. The path coefficients of each potential variable to dependent variable are PV (β=0.281), TSA (β=0.310), CFT (β=0.074), PR (β=-0.093).

6.1.1 Factors directly affecting PI

(1) PV

The results show PV is one of the key factors affecting PI. When consumers purchase virtual products such as online courses, they fully collect relevant information and compare different options and then obtain their personal PV to make decisions, which is consistent of previous research (Zeithaml, 1988; Wang, 2015; Chu, 2018; Hong, Zheng, & Zhou, 2019). When users make a judgment of PV, they compare and evaluate perceived benefits and losses, based on which they obtain the self-perceived value, and it ultimately drives users' intention to purchase the course on OEP.

Enlightenment for management: PV significantly affects PI. Therefore, in the formulation of marketing strategies, it is necessary to highlight the perceived benefits of courses on the OEP, so that users can perceive more value, gains and benefits. In this way, consumers can fully understand the benefits that the course can bring to them and clarify the value of the course when they choose their own products or share them through WM. This also requires the operators of the OEP and the producers of the courses to focus on refining the selling points of the course. At the same time, the target customers of the course need to be positioned at the stage of the course production, and the characteristics of the course need to be integrated into the content of the course. This also makes the course more targeted, reduces unnecessary promotion costs in marketing, and the targets of the course are refined, thus creating unique selling points. The comparison between perceived benefits and perceived losses finally form PV, which also provides a reference for classification management for the OEP.

According to the multi-group comparative analysis, no matter users once bought courses on OEP courses or not, their PV significantly affects the user's PI. Therefore, it is particularly important to impact the PI of users through PV.

(2) TSA

Through empirical analysis, TSA has a significant impact on users' PI, which shows that the TSA of online courses has become one of the key factors to enhance users' PI (Shu, 2016; Yang, 2016; Su, 2019). In the multi-group comparative analysis, it was found that users with and without experiences in buying course on OEP passed the significant test of TSA.

TSA means that the learning method on OEP is not restrained by time and space, allowing users to decide the content, progress, time and place of learning autonomously. The online course does not require users to spend time to go to the classroom to participate in the training. The recorded course allows the user to decide the time and place to study. Although the live course does not allow users to choose when to study but it is more interactive, engaging users and teachers to have in real time interaction and feedback.

TSA has brought about tremendous changes in the way of teaching. Since online learning breaks the limitations of time and space, online learning allows more users to learn and interact online simultaneously through networked terminal devices such as mobile phones and computers. The online course broadens the teaching method and carrier. The online method can combine many new teaching software and multimedia technology to enhance the results and entertainment of teaching.

Enlightenment for management inspiration: 1, TSA has expanded the target customer coverage of the OEP. The online learning is more convenient and faster, so the marketing of OEP can be targeted at users of offline learning by providing different learning experience. These users are also potential target consumers for OEP marketing.

2. The OEP and course producers should pay more attention to the characteristics of TSA, make full use of new technologies to improve user learning efficiency and convenience. Combining the popular 5G, virtual reality (VR), Internet of Things and mobile Internet technologies, the convenience brought by TSA can be fully explored for users on the OEP.

3. To learn with fragmented time should be allowed. TSA facilitates real-time tracking and feedback. New technologies, new features, and wearable devices allow users to participate in the teaching process without being constrained by time and space. Breaking the time limit also allows users to take advantage of fragmented time for phased learning.

(3) CFT

In the model of users' intention of purchasing courses on OEP, the CFT has a significant impact on users' willingness to buy courses, which indicates that CFT directly affects users' intention of purchasing courses on OEP (Li, 2016; Xu, Zhang, & Dong, 2018; Li, Zhang, & Hu, 2019). It can be seen that CFT is also one of the key factors that directly affect the willingness to purchase the course.

In the multi-group comparison analysis, for users who never bought online courses before, the CFT (β=0.205, p<0.001) significantly affects their PI, which indicates that they pay more attention to CFT of the online course. For users who once bought online courses before, CFT does not significantly affect their willingness to buy online course. Through the comparison of the two groups, it is found that CFT imposes different impacts on users with different purchasing experiences.

Because online courses are virtual e-commerce products, they generally exist in the form of video, text, and pictures. It is difficult for users to have an intuitive evaluation and feeling about the online course. It can only be understood through the relevant introduction of the course. However, the CFT provides users with the opportunity to understand the content, the instructor, the method of teaching, and the quality of the lecture in the course. The experience provided by the free trail of the course is more intuitive than the text and image, thus it is more helpful for users to make rational purchasing decisions.

Enlightenment for management: The OEP should provide more free trial services for users and improve the quality of CFT. The CFT reflects the confidence of the OEP and the course producer, which can help the user to understand the details of the course straightway. The CFT allows the user to intuitively understand the content, form, quality, etc. of the lecture, thus helping the user make the purchase decision. From the data analysis, CFT enhances the user's willingness to purchase. Therefore, the OEP should provide CFT service, pay attention to the quality of CFT, and help the user to intuitively feel the specific content and form of the course, thereby raising the sales conversion rate of the online course.

In the multi-group comparative analysis, CFT imposes different impacts on PI of users in two groups with different purchasing experiences. Among them, users who never bought online course before pay more attention to CFT. Due to the lack of similar purchase experience before, it is difficult for them to assume the subsequent experiences of buying an online course, so these users prefer to use CFT to have a taste of the online course. In marketing promotion, greater efforts should be made in promoting CFT recommendation to users who never bought online course before, to enhance their willingness to start buying courses.

(4) PR

This study has found that PR significantly affects PI, which indicates that PR is also one of the key factors affecting the willingness to purchase online courses (Wang, 2016; Wang, 2017; Xiang, 2018; Cui, 2019). In the multi-group comparative analysis, it was found that PR of users without purchasing experience has a significant negative impact on PI. PR of users with purchasing experience does not have a significant impact on PI. Users worry that the quality of the course may not meet their expectations since the online course is a virtual product the course, and they also worry that the they cannot achieve the purpose of learning through learning the online course, or they cannot complete learning all the course. Since the user understands the content of the course only through the course introduction on the website, there is no intuitive way to inform themselves of information about the course, so the user has fears and worries that hinders their intention to buy courses.

Enlightenment for management: 1. A 7-day return of goods without reasons can be offered. Users are allowed to request refunds under limited conditions, which reduce users' fears that the quality and content of the course cannot meet their expectations. This practice can reduce concerns of users, to enhance their willingness to buy online courses.

2. The function of online customer service can be added to improve the convenience of contacting customer service. Optimization of online customer service ensures that users can contact customer service when they are hesitant or have concerns, and the service can relieve their worries, answers their inquiries, and reduce users' concerns about the after-sales service.

3. The free re-learning service can be provided, which allows users to participate in the next course if they are not able to complete the current course, thereby reducing the user's fear of not being able to complete the course in time.

In the multi-group comparative analysis, for users without buying experience, their PR exerts a significant negative impact on their PI. Since the group of users never bought similar products before, their PR is more likely to high. However, for users with experience in buying online courses because they already have related buying and learning experiences, their concerns about the quality, content and learning arrangements of the course are no longer the key factors hindering them from buying online courses. In marketing, more attention should be paid to the reduction of PR of users who never bought online courses before, so as to increase the PI of this group of users.

6.1.2 Discussion on factors indirectly affecting PI

The PLS structural equation model of users' intention in buying courses on OEP shows that PU (β=0.304), PEU (β=0.349), and TSA (β=0.180) all significantly and positively affect the mediator variable, PV. Then, through PV, these above-mentioned factors further affect PI of users. PC (β=-0.242) and PR (β=-0.260) negatively affect the mediator variable, PV.

(1) TSA

Before conducting the group analysis, TSA significantly and positively affects users' PV, and then indirectly affects PI through PV (Yang, Zhang, & Man, 2012; Xuan, Dai, & Lin, 2018; TRI, 2019). Therefore, TSA is also one of the important factors that affect users' PI.

In the case of group comparison analysis, for users with experience in buying online courses, TSA significantly affects their PV, and indirectly affects their PI. However, for users who never bought online courses before, TSA does not significantly affect their PV. Users without related experience have more considerations about the content and quality of the course, and they do not prioritize time and space of learning the course when making their decisions.

Enlightenment for management: 1. Optimize learning function of TSA to enhance the user's PV, which indirectly affects their PI. Realizing TSA often relies on the wireless terminal learning software provided by the OEP, so that the user can be allowed to decide the content of learning and the supporting functions.

2. For the users who have the purchasing experience, the marketing should focus on the convenience brought by TSA. In the group of users with purchasing experience, TSA significantly affects the user's PI and PV. Therefore, it is necessary to strengthen the targeted publicity and advertisement for users with purchasing experience and optimize the convenience of self-learning functions to reduce the user turnover rate and improve the repurchase rate of users who have purchasing experience.

(2) PC

According to H6, PC has a significant negative impact on PV and then indirectly affects PI through PV. PC is also one of the important factors affecting users' PI (Cheng, 2006; Chen, 2016; Wang, Li, & Wang, 2017; Song, 2018; Dong, Zhou, & Mao, 2019). In the multi-group comparative analysis, regardless of the users' previous course purchase experience, PC has a significant and negative impact on PV.

Higher price of online courses can significantly affect users' PV of the course, and the time and effort spent on the course also affect users' PV. Therefore, reducing the PC of the user is not limited to pricing optimization of the course, and it also includes the improvement of learning mode of the course and the learning plan to adapt to the users' individual learning needs.

Enlightenment for management: 1. Price the course based on the price range accepted by the user. The pricing of the course should not be a unilateral pricing strategy by the OEP. On the contrary, it should be based on the user survey, and the pricing should be within the price range that can be accepted by users to boost sales, thus maximizing income for the OEP.

2. Provide personalized and targeted curriculum programs in line with users' knowledge reserve. According to the level of knowledge that the user has mastered and their individual time schedule, the course content can be appropriately divided into several course modules. This not only reduces the unit price of the course, but also allows the user to choose the course module that suits them. Users can choose to skip or temporarily not learn the content they have mastered, and directly learn what they need based on the course module.

(3) PU

From the analysis of the intention model in purchasing courses on OEP, it is concluded that PU significantly affects the user's PV, and then indirectly affects their PI. Therefore, PU is one of the important factors affecting PI (Ouyang, 2014; Yang, Jiang, & Ma, 2017; Fang, Lu, & Liu, 2018; Li & Wang, 2019). In multi-group comparative analysis, PU of users with and without purchasing experience significantly affects their PV.

On the OEP, the course needs to be more elaborated and exquisite, and the quality of the course content should be improved. In this way, users can perceive that the online course is conducive to improve learning efficiency and learning results and help them to acquire more knowledge. In addition, the learning process should be produced with better interestingness, enjoyment and relaxation because it is more conducive to enhancing the users' PV, thus affecting their PI.

Enlightenment for management inspiration: 1. Pay attention to the content of the course and target the selling point of how the course can improve the learning efficiency and learning effect. The OEP should continuously optimize the content of the course to improve the learning efficiency and learning effect of users. The OEP should also provide a high-quality and comprehensive curriculum introduction, in-depth description of the course's positioning, goals, academic analysis and teaching methods, which is more conducive to improving users' PU.

2. In the process of developing the course software, the OEP should pay attention to the usefulness and convenience of the software and to the effectiveness and convenience of the course content when arranging the course content.

(4) PEU

Before the multi-group comparison, PEU significantly affects users' PV, which is also consistent with previous research results (Liu & Tang, 2015; Liu, 2016; Bai, 2017; Liu, 2018). PEU indirectly affects PI by significantly affecting PV. Therefore, PEU is one of the factors that impact PI.

In the multi-group comparison analysis, PEU of users who do not have purchasing experience significantly affects their PV. PEU of users with purchasing experience does not significantly affect their PV. This also illustrates that users without purchasing experience are more worried about whether the methods and software provided by the OEP is easy to use. This group of users who have no purchasing experience are unacquainted with function modules of online course, such as learning module and customer service contacts module, so they tend to pay more attention to the way how the course is learned and the way how the software is used. Users with purchasing experience have owned a certain understanding of the way of course learning and software operation, so PEU does not significantly affect their PV.

Enlightenment for management: 1. Improve the ease of use of the learning software where the online course is provided. When developing the learning software and learning methods, the OEP should pay attention to the feedback from the users, develop the learning software and learning methods that are user-friendly and conform to the user's habits of operating software, thus enhancing the user's PI.

2. Continuously optimize the teaching methods and learning experience of online courses. The popularity of new multimedia technologies, 5G technologies, and mobile Internet brings more possibilities for holographic projection teaching, high-definition video teaching, and VR teaching. OEPs should focus on the convenience brought by new technologies and improve the ease of use of online courses.

3. Targeted dissemination and publicity with focus on PEU for users who have no experience in purchasing online courses. In the multi-group comparative analysis, PEU of users without purchasing experience significantly affects their PV, which indirectly affects their PI. This indicates that users who have no purchasing experience pay more attention to whether the

courses offered by online education courses are easy to learn and whether the software is easy to use.

(5) PR

Users' PR is significantly and negatively affected by their PV, a finding that confirms previous empirical research (Wang, 2007; Wan, 2011; Yang, Jiang, & Ma, 2017; Fang, Lu, & Liu, 2018; Guo, 2019). In the multi-group comparative analysis, the PR of users with different purchasing experiences significantly affects both their PV, which further explains that PR is one of the important factors influencing the user's intention to purchase online courses.

When users selecting courses on OEP, they worry that the quality of the courses cannot meet their expectations, the effect of the course cannot meet their expectations, and they also worry about the quality of after-sales service. Therefore, it is necessary to reduce users' PR to improve their PV, and indirectly improve user's PI, and this is a very effective and necessary measure.

Enlightenment for management: 1. Provide users with FCT opportunities to better inform them of the course. Through the FCT, users to get a certain understanding of the quality, learning form and learning style of the course, and then consider how to make corresponding decisions. This practice is beneficial to reduce users' PV.

2. Optimize the contact function and contact information of online customer service. In order to reduce some users' concerns about the after-sales service and how to use some course functions, the user's PR can be reduced by providing more convenient customer service contact, thereby enhancing the user's PV.

6.1.3 Discussion on WM

As a moderator variable of PV to PI, WM has passed the significant test and significantly and positively moderates the impacts from PV to PI. This is the same as the previous research results (Zhong & Zhang, 2013; Chen, Wu, & Zhang, 2017; Wang, Wang, & Yang, 2019). In the multi-group comparison, WM significantly moderates the impacts of PV to PI, so it can be concluded that WM is one of the key factors affecting the intention of users to purchase online courses. Intensifying efforts in building WM of the course is an effective measure to improve users' PV and PI.

Since WM is feedback from users who have previously purchased the course, it has reference significance for users who have not yet purchased the course. Users often refer to the relevant comments of the course before purchasing it and distinguish the authenticity of the comments and distinguish which comments can guide them. WM often provides users with a relatively objective feedback. Compared with the course introduction that is published by the OEP, WM is more authentic, especially in the case of purchasing virtual e-commerce product when WM is more informative and of greater reference value.

Enlightenment for management: 1. The OEP needs to pay attention to the accumulation of WM. If the OEP does not have any WM, it will be difficult to obtain the trust of users. Therefore, the accumulation of quality course feedback and comments provides users with reference for making rational purchasing decisions. Authentic WM helps to enhance the user's PV and PI.

2. Collect feedback about the course to improve online courses. The OEP can classify the WM when users comment or give feedback on the course, and specifically study the reasons why the user makes the comment to achieve the purpose of collecting user opinions to promote course optimization.

3. Timely feedback to users' WM, establish a good two-way interaction mechanism. When the user leaves the course feedback and WM, the staff of the OEP can communicate with the user in time to prevent from one-way communication. At the same time, this practice can offer users a sense of participation in curriculum building and better maintain the relationship between the OEP with customers.

4. Discover potential WM marketing objects. Discover the WM marketing objects who are willing to share for the second time that means that they are willing to share their learning experience with their friends and relatives and understand the user's feelings about the course through the user's comments. In this process, it can be discovered that users who are willing to do second-time-sharing, which is beneficial to the OEP to carry out low-cost WM marketing.

6.1.4 Discussion on users' age and education background

(1) Users' age

In the analysis of control variables, users' age significantly affects the PI (Gao, 2013; Chen, 2018). In the multi-group analysis, the user's age also significantly affects the user's PI, which indicates that the user's age is one of the important factors that affect the user's intention to purchase online courses.

The users' age significantly and negatively affects their intention to purchase online courses, which indicates that as the users' age increases, the intention to purchase online course will decrease. Users who are relatively young have a stronger learning atmosphere and a stronger curiosity, as well as a longer time span to extract economic rents from the investment in human capital. The OEP curriculum is a novel way of learning and is more easily accepted by the younger generation who are immersed in the learning atmosphere.

Enlightenment for management: Course marketing grouped according to the age of the user. Targeted promotion is conducive to improving users' willingness to purchase courses and user experience, while reducing invalid promotion and advertisement distraction for users. In the multi-group comparative analysis, this research also found that the user's age has a significant and negative impact on users' PI, further indicating that the user's age is one of the important factors affecting their willingness to purchase the course. The OEP can promote the course hierarchically according to users' age, which helps to increase the user's willingness to purchase the course.

(2) Users' education background

In the model of users' intention in purchasing courses on OEP course, users' education background significantly affects their intention to purchase the course, which is also in line with previous research results (Feng, Mu, & Zhang, 2008; Fan, 2015; TRI, 2019) and explains that user education background is one of the important factors that affect their intention in purchasing online courses.

In the multi-group comparative analysis, it was found that the education background of users without experience in purchasing online courses significantly affects their PI. The education background of users with purchasing experience does not significantly affect their PI. This shows that in the user group without purchasing experience, highly educated users make corresponding decisions through data collection and self-judgment. Users with purchasing experience have gained a certain understanding of online courses, so their education level does not significantly affect their intention to purchase courses.

Enlightenment for management: Increase efforts in the marketing promotion for users with higher education level. The OEP can use data analysis to understand whether the user has a purchase record, and OEP can also use its own and third-party database to analyze the user’s education level to determine whether the user without purchasing experience is highly-educated, and then launch a corresponding recommendation mechanism. Such a process can reduce unnecessary marketing expenses and achieve better promotion results.

6.2 Research recommendations

1. To ensure the quality of the course, provide WM for reference. PV significantly affects PI, and WM significantly and positively affects the impacts of PV on PI. Ensuring the quality of the course and enhancing the PV of the course are critical to enhancing PI. Users on OEP filter and select the course by the number of clicks, purchases, and WM. With these professional data indicators that are deprived from the course content, it is very difficult to truly judge the quality of the course. Selecting a course solely based on Internet data indicators is easily stimulated by marketing methods, resulting in the situation that courses are not suitable for some users who spend time and money, ending in poor learning results. Grasping the quality of the course, accumulating reputation through excellent courses, and accessing more loyal users, are opportunities for the OEP to form its own unique advantages and realize the sustainable development of the OEP.

2. According to the user group classified based on their purchase experience, recommend online courses through AI. Users with different purchasing experience have different salience in terms of CFT, PC, PEU, TSA and education, which requires refining user portraits and labels,

and recommending course in different groups and layers. OEPs can enhance the alignment of content diversification and individualized needs and analyze users' needs and recommend courses in a targeted manner through AI technology to enhance users' PI.

3. Optimize TSA function and use 5G, VR, and AR to enhance the user experience. TSA significantly affects users' PI. PU and PEU significantly affect PV and indirectly affect users' PI. Therefore, improving TSA, PU and PEU helps to increase intention in purchasing courses. The online education program allows users to learn anytime, anywhere, while taking advantage of fragmented time, and their learning is no longer limited by the location of the class, making the learning process easier and more convenient. Utilize new technologies such as 5G, VR, and AR to upgrade the OEP to provide users with a learning environment of "learning at any time and self-control progress".

4. With cloud services, big data technology to reduce the price of the course. PC significantly and negatively affects PV and indirectly affects PI. Providing online course at preferential prices is conducive to improving the user's intention to purchase the course. The application of cloud services and big data technology can allow an increasing number of users to learn online courses, provide better service for OEP users and greatly reduce the marginal cost.

5. Provide more CFT, to reduce users' PR. Free trials in advance of the course helps users understand the content, quality, applicability, etc. about the course, and helps customers make their purchasing decisions. In particular, for users who never bought online courses before, CFT can be provided to increase their PI. OEPs such as Taobao OEP, Tencent OEP, and CCtalk all offer opportunities for free trial to enhance purchase rates.

6.3 Research innovation

(1) Innovation in data sources. The sample data in this research is all from user feedback in a real business environment. The main data comes from user surveys of real OEPs such as DataCastle, Tencent OEP, and Taobao OEP, rather than using student questionnaires to obtain sample data, therefore this study restores consumer behavior in real business scenarios to the

largest extent. Compared with the way of student questionnaire, this study is more persuasive, enjoys greater commercial reference value, and can give some guidance to OEP companies and practitioners.

(2) Integration and innovation of the research model. The model of users' intention in purchasing courses on OEP of this study integrates and innovates the TAM, PV and PR theory. According to the situation of China's OEP, two situational variables, FCT and TSA were introduced. The moderator variable, WM and control variables were also added to expand the scope of the model and improve the theory of PV.

(3) Innovation in research methods. In this study, the PLS-SEM research method was used to construct a model for researching factors influencing users' intention in purchasing courses on the OEP and conduct related tests. Then group discussions were carried out based on if users have experience in purchasing courses on OEP before. PLS multi-group analysis (PLS-MGA) was used for multi-group comparison analysis to further discuss the relationship between different latent variables in the model in two different groups with different purchase experiences, to explore the factors involved in the PI and the impacts strength of the corresponding factors in two groups.

6.4 Limitations and outlook

Based on the literature review and the research results of previous researchers, this study carried out the research on factors influencing users' intention in purchasing courses on OEP in China, achieving significant results. However, due to objective restrains such as the shortage of manpower, the lack of material resources, time and energy, the scope of this study is still very limited with some shortcomings, but these shortcomings can also be interpreted as suggestions for further research in the future.

Point 1: Future research on economic returns of students.

Future research can consider the potential variables of economic returns and investigate the income differences gained by users of online courses before and after learning to study whether the economic returns and income differences before and after learning have a relevant impact on their purchasing decisions. In light of the diversity of online course types, this survey can also understand whether the economic returns affect the user's choice of course type to enrich the research content in related fields.

Point 2: Optimization of data collection methods and sample size.

The data of this survey came from online questionnaires issuing and collection, which means that all questionnaires were replied and collected at one time point. Therefore, the number and representativeness of the questionnaire are somewhat one-sided. Under the trend of digitization and big data, researchers can consider working with OEP companies to track the behavior of users on the platform and record user portraits, so as to obtain larger and more comprehensive data samples to analyze users' intention in purchasing courses.

Point 3: Exploration of more latent variables and research methods.

Subsequent studies can combine qualitative research with quantitative research. In the process of empirical research, deep communication can be conducted through focus interviews to discover more latent variables. The combination of the two research methods is conducive to making up for the lack of quantitative research. Through in-depth interviews with users, more innovative and latent variables can be obtained to improve the research.

Point 4: In-depth longitudinal study.

This study focuses on users' intention to purchase online course, and the follow-up study can focus researching on the user's purchase behavior. Then, by tracking the entire behavior process from browsing, registering, using, purchasing, repurchasing to customer loss, users' behavior is continuously studied to accurately understand the information of users' life cycle behavior.

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Appendix

Research Questionnaire for Influencing Factors of Online Education Platform Course Purchase

Dear Sir / Madam,

Thank you very much for taking the time to participate in this survey. This questionnaire is purely for academic research, aiming at investigating the factors that influence your intention to purchase courses on online education platforms (OEPs). There is no right or wrong answers. You are kindly requested to fill it out according to your real situation. This survey is anonymous, and strictly follows the principle of confidentiality, only used for academic research purposes. Your opinion has a significant impact on the results of this research. Thank you again for your support.

Congratulations: Happy new year and all the best.

1. Do you have experience using OEPs? [You can choose only one option]*

○Yes ○No

2. Gender [You can choose only one option] *

○Male ○Female

3. Age [You can choose only one option] *

○Below 18 ○19-25 ○26-35 ○36-45 ○Above 46

4. Education background [You can choose only one option] *

○High school (technical secondary	○Diploma's degree	○Bachelor's degree	○Master's degree	○Ph.D

school) and below

5. Occupation [You can choose only one option] *

○Student	○Private sector	○Public institution	○Civil servant	○Social group	○Company owner and individual business	○Others

6. Annual income (unit: thousand) [Multiple choice] *

○Below 30	○40-100	○110-200	○210-300	○Above 310

7. Which OEPs have you used (If you have experience using online education platform, please continue) [You can choose more than one options] *

☐NetEase Cloud Class (ke. Youdao)	□Hujiang Online School (including CCtalk)	□Taobao Education (Taobao College)
□Tencent Classroom	□Baidu Chuanke	□YOUKU Academy (Youku education channel)
□YY Education	□Duobei	□Gxtaoke
□Sina Open Class	☐Others ________________	

8. Have you purchased a paid course from an online education platform? [You can choose only one option] *

○Not planning to buy	○Planning to buy	○Have purchased and learning	○Have purchased and learned

9. What are the content of your courses? [You can choose more than one options] *

□ Certificate	□Professional skills	□Training on upgrade from junior college student to university student or undergraduate to postgraduate	□ Civil servant exam training
□English training	□Hobbies	□ Others ________________	

10. Perceived value (1=Highly disagree ～ 7=Highly agree) [Matrix scale] *

	1	2	3	4	5	6	7
Compared to the money I paid, it is worth buying online courses.	○	○	○	○	○	○	○
Compared to the time I paid, it is worth buying online courses.	○	○	○	○	○	○	○
Compared to the effort I put in, it is worth buying online courses	○	○	○	○	○	○	○
I think buying online courses is valuable and meaningful.	○	○	○	○	○	○	○

11. Word-of-Mouth (1=Highly disagree ～ 7=Highly agree) [Matrix scale]*

	1	2	3	4	5	6	7
Before I buy an online course, I will refer to the relevant reviews of the course.	○	○	○	○	○	○	○
The review in the online course review area is more	○	○	○	○	○	○	○

authentic.							
The review in the online course review area is more reliable.	○	○	○	○	○	○	○
The review in the online course review area is more objective.	○	○	○	○	○	○	○

12. Perceived Risk (1=Highly disagree ～ 7=Highly agree) [Matrix scale]*

	1	2	3	4	5	6	7
When I buy an online course, I am concerned that the quality of the course is not as expected.	○	○	○	○	○	○	○
When I buy an online course, I am worried that the course will not achieve the purpose of learning.	○	○	○	○	○	○	○
When I buy an online course, I worry about not being able to complete the course.	○	○	○	○	○	○	○
When I purchase an online course, I worry that after-sales service is not guaranteed.	○	○	○	○	○	○	○

13. Perceived Cost (1=Highly disagree ～ 7=Highly agree) [Matrix scale]*

	1	2	3	4	5	6	7
I think online courses are relatively expensive.	○	○	○	○	○	○	○
Buying online courses will cost me more money.	○	○	○	○	○	○	○
Online courses have not shortened my time and effort to acquire knowledge.	○	○	○	○	○	○	○

Choosing the right online course is a waste of my time and energy.	○	○	○	○	○	○	○

14. Perceived Usefulness (1=Highly disagree ～ 7=Highly agree) [Matrix scale] *

	1	2	3	4	5	6	7
I think online courses can improve my learning efficiency.	○	○	○	○	○	○	○
I think online courses can improve my learning result.	○	○	○	○	○	○	○
I think online courses can help me gain more knowledge.	○	○	○	○	○	○	○
I think online courses will make my learning easier.	○	○	○	○	○	○	○

15. Perceived Ease of Use (1=Highly disagree ～ 7=Highly agree) [Matrix scale] *

	1	2	3	4	5	6	7
I can easily find the courses I need through the online education platform.	○	○	○	○	○	○	○
I can easily use the online education platform to learn my course.	○	○	○	○	○	○	○
I can easily contact the supplier of the online course.	○	○	○	○	○	○	○
I can easily use the new features and new versions of the online education platform.	○	○	○	○	○	○	○

16. Course Free Trial (1=Highly disagree ～ 7=Highly agree) [Matrix scale]*

	1	2	3	4	5	6	7
Online courses that support free trials help me make more	○	○	○	○	○	○	○

informed buying decisions.							
If the online course that I listened to meets my expectations, my willingness to buy will increase.	○	○	○	○	○	○	○
If the way of lecturing can attract me, my willingness to buy will increase.	○	○	○	○	○	○	○
Whether the online course supports trial affects my purchase intention.	○	○	○	○	○	○	○

17. Time and space autonomy (1=Highly disagree ～ 7=Highly agree) [Matrix scale] *

	1	2	3	4	5	6	7
I can decide what I want to learn while studying online.	○	○	○	○	○	○	○
I can decide on my own learning progress while learning online.	○	○	○	○	○	○	○
I can decide when I want to study while learning online.	○	○	○	○	○	○	○
I can decide where I want to study while learning online.	○	○	○	○	○	○	○

18. Purchase Intention (1=Highly disagree ～ 7=Highly agree) [Matrix scale] *

	1	2	3	4	5	6	7
In the future, I will try to purchase paid courses on the online education platform.	○	○	○	○	○	○	○
In the future, I will continue to purchase paid courses from OEPs.	○	○	○	○	○	○	○
If online courses are what I need, I would love to buy.	○	○	○	○	○	○	○

I would recommend quality online courses to friends.	○	○	○	○	○	○	○