The Moderating Role of e-WOM

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Except for perceived fee, which has a negative effect on perceived value, the results demonstrate that all hypotheses of latent correlations in TAM and VAM were strongly significant. Furthermore, attitude and perceived value have a significant role in determining consumer adoption of e-learning. Consumers' perceived value will be driven by the high and low levels of the moderating influence of e-word of mouth, influencing their intention toward e-learning. Since e-learning is an effective sustainable education system, the result of this study can provide a good solution to facilitate e-learning in current and future conditions.

e-learning | technology acceptance model | value-based adoption model | e-word of mouth | perceived value

1. Technology Acceptance Model (TAM)

Reference [1] developed the TAM model in predicting consumers' attitudes toward new technology. PU and PEOU are the model's core constructs for determining consumer attitudes toward new technologies. In the research subject of information technology, TAM has been thoroughly studied and recognized. Therefore, TAM is a powerful model widely used in assessing the consumer acceptability of new technology services in ITC [2]. However, given the current situation, the variables in TAM have become simple and have a limited ability to predict a customer's psychology during decision-making in a practical context [3]. TAM has been extended many times to apply to different technologies. In the current context, e-learning is a topic that attracts a large number of researchers interested in the use of various new technologies. Reference [4] conducted a systematic review of the use of artificial intelligence (AI) in online education. Additionally, reference [5] emphasized the necessity of using AI in e-learning to better user experience and personalize learning material recommendations in order to increase learning efficiency and sustainable learning environments. Among them, TAM is still the most frequently used to predict adoption intentions for a variety of technologies, particularly in the application of technology to support learning performance. Reference [6] utilized an extended TAM to assess teachers' intentions to incorporate augmented reality and virtual reality technologies into their classroom teaching. Additionally, reference [7] used the TAM-3 model to determine the desire of participants in e-learning to use cloud storage. On the topic of IE, **Table 1** summarized some of the research that used the TAM model. The proposed variables in their extended TAM research model mainly focus on: subjective norms, PE, self-efficacy, and some quality-related factors such as service quality and content quality. The study results show that applying TAM to the research model in the field of e-learning is completely appropriate. This study proposes an extended TAM model by combining it with VAM to emphasize the role of PV in research into new technology applications.

Table 1. Previous studies review.

2. Value-Based Adoption Model (VAM)

According to [8], adoption intention can be predicted through PV. PV was defined based on a balance of benefits and sacrifices and the classification of motivations into extrinsic and intrinsic subsystems. Consumers gain benefits that are not just useful but also thrilling and enjoyable. Sacrifices, which include both monetary and non-monetary aspects, are the prices users incur while utilizing new technology. These costs include money, time, and the intangible costs associated with attempting and implementing new technology. The VAM was designed in response to the limitations of TAM, considering factors affecting PV. PV is beyond the point of maximum value. More specifically, TAM was proposed based on PU and PEU variables to explain and predict customer intent, while the VAM is based on perceived benefits and sacrifices. This includes both positive, and negative influences to bypass the limitations of TAM. Customers can assess the value they receive, resulting in a more accurate intention to use new technology [9]. The VAM model has been merged with other models and applied in a range of studies based on consumer value perspectives. Reference [9] proposed TAM and VAM be integrated into applications of Internet of Things (IoT) smart home services; [10] devised the Acceptance and Use of Technology (UTAUT) and the VAM in the context of AI research; and [11] developed an integration model of VAM and transaction cost theories. Considering that, this research proposes a combination of TAM and the VAM to support each other. The illustration of the research framework for this study is shown in **Figure 1**.

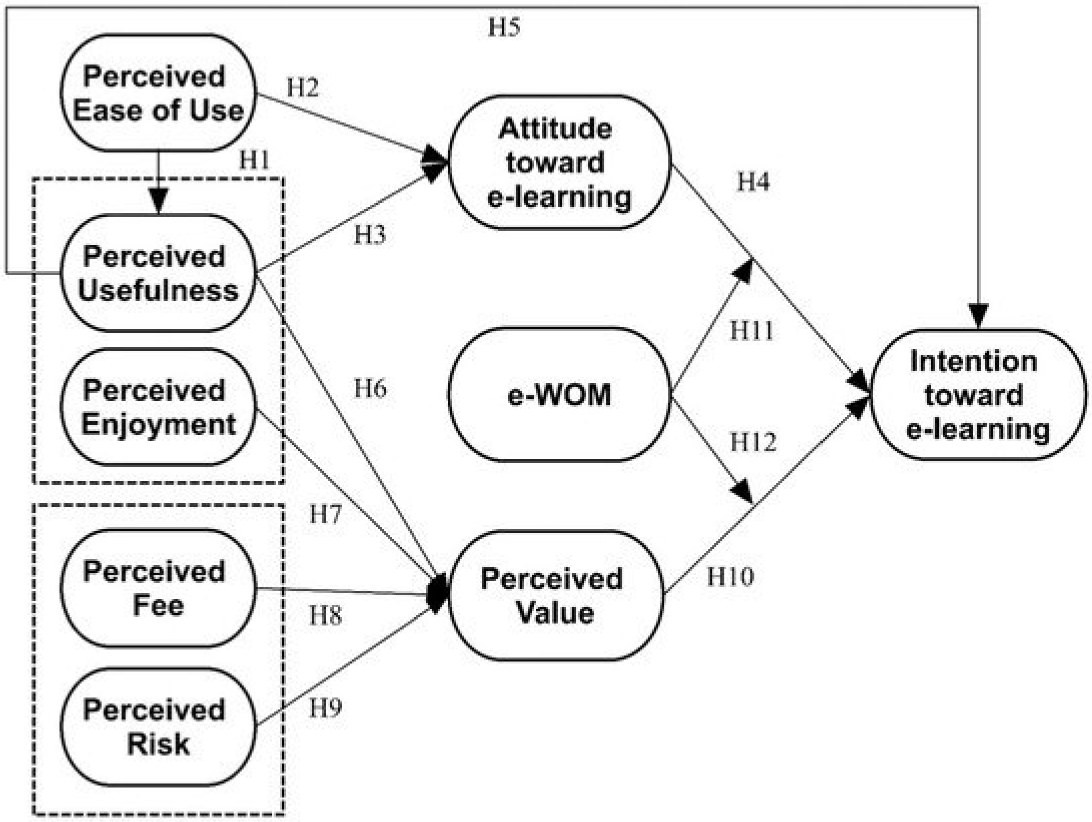

Figure 1. Conceptual proposed model.

3. Relationships among Variables in TAM

Many prior studies applied TAM to investigate which factors affect e-learning orientation. These studies have proven that PU and PEU are two critical variables for understanding customer behavior in the application of new technologies. PU is the customer's perception of how using the technology will help them improve and gain more benefits [12]. Besides that, PEU is defined as "the degree to which a users feel that utilizing a e-learning system will be uncomplicated". Rather than spending time learning how to utilize the system, users can begin using it immediately, reaping the benefits of learning such as time, money, and effort savings. This enhances their PU in association with the e-learning system; the more user-friendly the system, the greater the PU [13]. Additionally, the positive effects of PEU on PU have been demonstrated in e-learning systems [14]. According to [15] attitude is defined as a psychological emotion that is channeled through consumers' assessments of the innovation. When consumers' perceptions of these two constructs improve, their ATE is more aggressive. This could also boost a user's receptivity to an e-learning system. In the context of e-learning, both PEU and PU have been proven to have a considerable positive effect on ATE [16][17]. In TAM, intention is essential in determining how new technology is actually used [12]. PU and PEU also have a key role in customer ATE. Besides, consumers' views that adopting an e-learning system will result in positive results for their learning performance, and the positive influences of PU and PEU drive IE in this study [18]. Additionally, the influence of ATE on IE has been confirmed [19].

4. Perceived Benefits and Perceived Sacrifice in VAM

4.1. Perceived Benefits

Reference [8] proposed VAM with two antecedent factors: perceived benefits and perceived sacrifices to assess PV. Accordingly, in this study, we defined perceived benefits including PU and PE. In the e-learning context, the degree to which users feel that learning through an e-learning system will be able to enhance their knowledge and help them accomplish the goal was described as PU. For this reason, consumers may consider the benefits of using e-learning to be greater than what they have to pay. Reference [20] found that PU has been considered an important determinant of PV. Some recent research [21][22][23] has found that the relation of PU to PV is fully significant.

Many researchers have suggested that when a user experiences more enjoyment using an IT system, he/she has increasingly intense motivations to interact with IT [24]. In this research, PE is referred as to the consumer's self-consciousness of fun, pleasure, and delight when participating and interacting in an e-learning system. Besides, while PU plays an important role in the utilitarian dimension of PV, PE is an essential dimension in e-learning users' perception of hedonic PV [25]. E-learning systems should be designed to provide a pleasant learning experience, an interesting method of learning, and appealing technology because consumers do not want to use a system that causes them stress or fatigue [26]. According to [27][28][29], PE has a significant positive impact on PV.

4.2. Perceived Sacrifice

The intention of the behavior of consumers through new technology services is influenced by the value they received from the service, which is a perceived fee (PF) [30]. If the value they get from e-learning is higher than the costs they spend, then purchase intent will be formed. If the value is lower, they will refuse the service. In the context of e-learning, service providers have to take care of the balance between expenses and the value that consumers receive. The costs include not only money but also other factors such as time and effort [8][31]. According to [24][32] the degree of PF has a considerable negative impact on customers' PV.

Additionally, the financial costs and the popular opinion of using a technological service like e-learning limits the spread of new technology [33]. The financial risks include the original purchase price and maintenance costs [34]. When consumers make purchase decisions, they are generally concerned about the product's efficiency and the financial consequences of the purchase, especially with new technologies such as e-learning [28]. This concern includes the perceived risk (PR) [29][35]. PR often arises from system hackers targeting the poor security of the system in order to steal consumer information such as personal information, credit card details, etc. These risks have a strong negative impact on consumer IE. This is a problem service providers should prioritize [28][29]. Thus, the PR of adopting e-learning will affect PV.

5. Perceived Value on Intention toward E-Learning

The possibility of a consumer purchasing a specific product in the future is measured by purchase intention [36]. Similarly, when consumers sense the worth of a product or brand, they are more likely to acquire it [28]. Consumers attempt to achieve the maximum benefit. PV is reflected by comparing benefits and sacrifices and forming an intent based on those comparisons. Moreover, consumers can shift their attitudes and emotions from the benefits of the product and create PV. Thus, if consumers can receive trustworthy PV when they purchase e-learning services, the services will bring many benefits for an e-learning institution such as creating a good brand image, the loyalty of consumers, profit, and competitiveness. In the e-learning context, PV is proportional to the intention. The higher the value, the greater the intent [37][38]. Research has indicated that PV has a strongly significant influence on IE [39][40].

6. The Moderating Role of eWOM

Reference [41] have defined eWOM as the positive or negative reviews, and comments of potential users or actual users about a product or a company via social networks or online tools. Recently, with the rapid growth of social networks, consumers have had the tendency to look for information and suggestions from others. They initially find information from those who are in close relation to them such as family members, friends, and colleagues [42], then, they search for information more widely. Usually, they search for information from those who influence them or internet influencers. The research of [43] pointed out that consumers rely more upon user-generated eWOM than firm-generated communications. Moreover, in social media channels, both the quality and quantity of eWOM impact consumers' purchase decisions [44]. Thus, this study only considered user-generated positive eWOM to explore the moderator role of eWOM. Previous studies had shown the positive influence of eWOM on IE [45][46][47], and positive eWOM will shape consumer ATE [48]. Furthermore, the study of [49] indicated that eWOM has a strong relationship with PV. According to [50], when customers have a favorable attitude toward online lecture websites, they are willing to recommend the e-learning course to others in their social networks. According to [51] students' e-learning directly impacts eWOM. This proves that when the strong ties of eWOM give a high recommendation about an e-learning system or e-learning service the overall value will increase value perception among consumers.

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