Article

Effect of Prior Gameplay Experience on the Relationships between Esports Gameplay Intention and Live Esports Streaming Content

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Abstract: This study examined the effect of prior experience with esports gameplay on its antecedents and consequences. Prior experience is considered a significant factor in consumers' intention and behavior, and in gameplay engagement it is considered the amount of gameplay time. While esports consumers are heterogeneous, only a few esports studies have been conducted. Thus, this study focused on prior esports gameplay experience to explain consumers' behavior better and examine antecedents, esports gameplay intention, and live esports streaming content across two groups (i.e., high and low frequencies of esports gameplay). Data were collected via an online survey in Amazon Mechanical Turk (M-Turk) from esports consumers who engaged in esports gameplay and live-streaming. One-third of the median cases were excluded to create two groups designated by weekly esports gameplay hours. The results revealed different patterns in the two groups. Specifically, esports gameplay had no effect on engagement in live esports streaming content for consumers who played esport games frequently. However, gameplay intention predicted live esports streaming content engagement successfully in the group who played infrequently. These findings contributed to (1) esports research by demonstrating consumers' heterogeneity, and the (2) extension of technology acceptance and use research in esports engagement by identifying the role of prior gameplay experience.

Keywords: esports; gameplay; live-streaming; prior experience; gameplay time

1. Introduction

The esports industry is growing rapidly and has captured gamers' attention. According to Newzoo [1], a market analytics firm that covers gaming and esports, esports global revenues were estimated at $1.1 billion in 2020, and are predicted to generate $1.27 billion in the coming year. The fast-growing esports industry has captured not only the attention of gamers, but also that of scholars with various viewpoints. Esports research is necessary for esports business sustainability because of the possibility of consumers' fluidity in this dramatically emerging context. Specifically, Twitch is the most successful live-streaming game platform that grew with the emergence of the esports industry. The concept of watching other persons' gameplay was less familiar to the consumers. However, esports fans' consumption of gameplay by watching both the streamers' live streaming and the broadcasts of esports events are the primary phenomena in the esports context. Thus, understanding esports consumers is essential to enhancing the sustainability of esports firms such as the developer-companies' live-streaming platforms. To explain the recent esports phenomena, studies of esports have been conducted across diverse disciplines, such as sport management, gaming and gambling, and mental

wellness [2–6]. In sport management, Jang, Kim et al. [7] identified social atmospheric elements (i.e., social density, suitable behavior, similarity, cosplay, and cheering behavior) to measure esports event participants' perceptions. The researchers found that all five factors influenced affective responses and intention to re-visit esports events in the future directly and indirectly, respectively. With respect to esports sport simulation gameplay in Spain, García and Murillo [2] investigated perceptions of participating in simulated sport esports games and traditional sports. They found different patterns for sport simulation esports games and their intensity. With respect to esports online spectators' motivation, its dimensions and scale were developed based upon the esports context's uniqueness [8,9]. Qian, Wang et al. [8] developed a measuring motivation associated with esports spectators. Qian, Zhang et al. [9] provided the foundational knowledge on various attriutbes affecting esports spectator consumption by developing the Scale for Esports Spectator Demand. For general esports gameplay engagement, Jang and Byon [3] proposed the Esports Consumption (ESC) model, which includes esports gameplay intention's antecedents and consequences from the perspective of technology acceptance. "Performance expectancy is defined as the degree to which an individual believes that the technology will be useful in daily life" (p.4) [3]. While the backbone of the technology acceptance models consistently encompasses performance expectancy, which benefits from using technology [10,11], these "benefits" derived from esports gameplay might not be relevant to esports gameplay. Jang and Byon [3] found that hedonic motivation, price value, effort expectancy, and flow predicted the intention to engage in esports gameplay, and this intention affected actual gameplay behavior and the intention to consume esports media. Jang et al. [4] extended the consequence of esports gameplay intention by distinguishing streamers' live esports streaming content and esports events broadcast from esports media consumption. In the complex combination of consumption in the esports context, Jang and Byon [3] and Jang et al.'s [4] findings indicated that esports gameplay consumption needs to be highlighted as the focal consumption that leads to other types of consumption, such as watching other gamers' gameplay via media.

While recent esports studies have explored diverse disciplines and explained esports phenomena, only a few esports consumers' segmentation studies of gameplay engagement has been conducted. Jang and Byon [12] described new categories in the esports game genre with which to cluster esports gamers. Further, esports consumers' gender was examined as a moderator to determine the ESC model's utility [13]. To extend cluster studies of esports consumers' esports gameplay, prior experience in esports gameplay may need to be emphasized. Fishbein and Ajzen [14] indicated that prior experience should be considered to understand customers' experience. Thus far, consumers' prior experience has played a role in consumer segmentation, according to Venkatesh et al. [15], who reviewed citations of studies that introduced evidence of the unified theory of acceptance and use of technology (UTAUT), which includes prior experience as one of the important moderators. Venkatesh et al. [15] indicated that consumers' prior experience moderates the focal determinants (e.g., hedonic motivation, price value, habit) of using technology and its intention in information systems (IS) and other fields. For example, consumers who have ample prior experience using a particular technology may feel more comfortable when they use new technology than those who have less prior experience. Customers' segmentation by prior experience was one of these studies' implications [12–15]. Based upon the differences between customers' segmentation, the research model's utility was verified so that practitioners can create more tailored strategies according to the customer segment's features. Traditionally, gamers are distinguished as hardcore or casual [16]. Juul [16] indicated that a hardcore gamer has different motivations, amounts of gameplay time, and game type preference than does a casual gamer. Gameplay time has been considered one of the important elements in segmenting gamers. For example, Manero et al. [17] identified four gamer clusters based upon gameplay frequency: Well-rounded gamers (very high frequency); hardcore gamers (above average frequency); casual gamers (less than average frequency),

and non-gamers/occasional gamers (very low frequency). The authors indicated that many researchers agree that identifying different gaming profiles can contribute to better game design, and gamer segmentation should be based upon the time spent in gameplay. Further, they used perception-based self-reports to measure gameplay time and asked how often their respondents play games with a 7-point Likert scale that ranged from "never" to "daily." While there are merits in using self-reports, such as their greater bandwidth compared to an objective measurement, an actual time measurement may have greater fidelity [18].

The purpose of this study is to examine the effect of prior esports gameplay experience according to gameplay time on the relationship between esports gameplay intention's antecedents and consequences. The gameplay time was measured as actual esports gameplay time per week. The clusters were divided by conducting a median split and deleting responses around the median to separate high and low frequency groups.

2. Theoretical Background and Hypothesis Development

2.1. Technology and Prior Experience in Esports

Technology is essential in esports because all esports games are video games. Prior experience has been considered a significant moderator in research on technology use [19,20]. Therefore, prior experience in engaging in esports gameplay may also serve as a criterion for heterogeneous esports consumer clusters.

Consumers must use electronic devices to play and watch esports games. Further, advanced technologies affect diverse aspects of the esports industry and research. For example, monitoring and securing financial transactions have been essential in the growth of esports, and industry practitioners have found solutions in new technologies [21]. For example, to attract potential investors and create a stable market, the security of prize distribution and funds withdrawal must be protected from potential fraud or hacking. Blockchain technology makes transactions more secure by blocking any hacking without the entire data chain. Other technologies, such as cryptocurrencies or smart contracts, also reduce the probability of fraud or hacking [21]. For example, Rothman [22] focused on intellectual property (IP) policies in new technologies in the context of esports. The rapid growth of esports and video gaming has increased the pace of changes in the context of computer technology and Internet applications. Dedicated esports betting websites have grown based upon this advanced technology [23]. As such, gaming equipment firms, media firms, esports event organizers, professional esports gamers, and streamers make a profit because of esports games' popularity. However, without proper technology, it would be impossible to reduce fraud attributable to hacking. Hence, diverse technologies to do so are vital and are used widely in the esports industry.

With respect to the use of technology, prior experience has been adopted as a moderator. For example, Sun et al. [19] adopted perceived behavior control and subjective norm based upon prior experience with the UTAUT model to predict IT use in China and found a significant effect of the factors related to prior experience. Workman [20] examined the moderating effect of previous experience with new technology in social media and smart applications with the UTAUT model. The author found a significantly different effect depending upon previous experience as a moderator of the intention to use social media and smart applications and indicated that a technology use model with a single dependent variable could be hazardous.

Prior experience in the context of gaming and esports is the experience of gameplay. Some esports consumers may have considerable experience playing esports games, while others may have little experience. According to Jull [16], hardcore gamers are individuals who spend considerable time and money on gaming. Because these gamers are very enthusiastic about improving their in-game performance, they spend a tremendous amount of time to achieve that goal. Manero et al. [17] indicated that one of hardcore gamers' primary characteristics is that their gameplay time is likely to be higher than that

of general gamers. On the other hand, casual gamers can be defined as individuals who spend less than the average time in gameplay and do not invest much effort to increase their gaming skills or win. Instead, they are likely to play games simply to enjoy the pastime with friends and are less competitive [16]. Based upon previous literature, this study defined prior experience as high/low frequency of esports gameplay (i.e., hardcore and casual gamers).

2.2. Prior Experience in Esports Gameplay

Given that esports consumers are gamers [24], and esports gameplay consumption may lead to other types of consumption [3], the technology acceptance approach to esports consumers' gameplay behaviors needs to focus on esports consumption. Thus, individuals who have no experience with esports gameplay may watch and follow esports-related broadcasts rarely [3].

Specifically, technology is inevitable in the context of esports, particularly in esports gameplay, which uses gaming hardware [3]. Not only technology is used to engage in esports gameplay, but it is also used to watch live esports streaming content and events broadcasts [4] through such devices as mobile phones and personal computers. Esports are electronic games that use technology in the connection between users' interactions, such as gaming hardware and visual feedback (e.g., computer monitor or television) [3]. Broadly, gaming consoles (e.g., Xbox, PlayStation), personal computers, and mobile phones are considered gaming hardware and mobile esports leagues have grown as mobile technology's performance has increased [1]. In video game research, virtual reality or motion-based gaming technologies have attracted the attention of scholars in technology and gaming [25]. Jang and Byon [3] focused on the technology acceptance elements to explore esports consumers' gameplay intention and the relationship between esports gameplay and watching esports media as suggested by the ESC model. According to previous research, prior experience is considered a significant moderator in research on technology use [19,20]. Thus, prior experience in the esports context may also lead to differences across the two groups based upon high/low frequency of esports gameplay.

Hypothesis 1: *There are different patterns between the two groups in the relationship between esports gameplay intention and its determinants based upon prior experience defined as the frequency of esports gameplay.*

2.3. Prior Experience with Live Esports Streaming Content

With respect to esports media consumption, streaming platforms such as Twitch have been considered by the hub of esports media consumption because of the advances in technologies [4]. Streaming technology plays video files without downloading them. With the advances in streaming technology, top media services, such as Netflix and Hulu, offer streaming services directly to viewers via the Internet. In addition, the popularity of live-streaming gaming services, such as Twitch, have been eclipsed by popular gaming streamers, such as Ninja, that are considered among the new influencers in the context of esports [26]. Jang et al. [4] distinguished live esports streaming content from esports events' broadcasts and indicated that the two-way communication based upon massive live chat technology between streamers and viewers is one of the key differences between streamers' live-streaming and esports event broadcasting. Thus, such technologies as personal broadcasting equipment for individual Internet streaming and live chatting technology may have supported the rapid growth in esports media consumption. The authors also supported the relationship between esports gameplay intention and live esports streaming content consumption. Qian, Wang et al. [8] developed the Motivation Scale of Esports Spectatorship, which included esports gaming skill improvement, game knowledge, and skill appreciation. Their findings indicated that improving esports gameplay skills and knowledge may motivate esports spectatorship. Thus, prior experience in gameplay may produce differences in esports content live streaming. For

example, if consumers are novices and have little prior experience playing esports games, they need to watch esports content live streaming more to improve their skills. In contrast, consumers who play esports often and are highly skilled already may be less motivated to watch live esports streaming content. On the other hand, consumers with significant prior experience may want to watch more live esports streaming content because they can enjoy it better based upon their ample background knowledge about the esports game. However, given that prior experience with technology makes a difference in its use [19,20], high/low frequency of prior experience playing esports games may also make a difference in live esports streaming content's use.

Hypothesis 2*: In the relation between esports gameplay intention and live esports streaming content, there are different patterns across the two groups based upon the frequency of prior experience in esports gameplay.*

3. Methods

3.1. Data Collection Procedure

Data were collected from Amazon Mechanical Turk (M-Turk). Peer et al. [27] indicated that a 99% survey acceptance rate could be one criterion of the comparatively reliable quality data in social science research. Thus, data were collected from adult participants in the United States with 99% approval rates with a minimum of 100 previously accepted responses. In addition, screening questions were used, such that only those with two experiences, esports gameplay consumption and esports media consumption, were allowed to participate in the survey.

3.2. Instruments

The screening asked two binary questions about esports gameplay experience and experience watching live esports streaming content. The participants who answered "yes" to both screening questions were allowed to continue to the main questions. The moderators asked the participants about their actual esports weekly gameplay time to divide them into high frequency and low frequency groups. To determine clear differences between the two groups, one-third of the cases around the median were excluded [28]. For the six antecedents and esports gameplay intention, seven variables with 23 items were adopted from the ESC model's scale [3]: Hedonic motivation (3 items); habit (4 items); price value (3 items); effort expectancy (4 items); social influence (3 items); flow (3 items), and gameplay intention (3 items). The questions were answered on a 7-point Likert scale that ranged from (1) "strongly disagree" to (7) "strongly agree." Lastly, an open-ended question asked about the actual number of hours per week that the participants watched live esports streaming content (see Table 1).

Table 1. Indicator Loadings (*λ*), Construct Reliability (CR), Average Variance Extracted (AVE) for the Variables and Items.

Variables	High Frequency (n = 304)	Low Frequency (n = 309)
Hedonic motivation (CR/AVE)	0.81/0.59	0.86/0.67
HM1: Playing my favorite esports game provides me with a lot of enjoyment.	0.82	0.73
HM2: I am pleased when I play my favorite esports game.	0.67	0.84
HM3: I enjoyed playing my favorite esports game because it is exciting.	0.80	0.87
Habit (CR/AVE)	0.78/0.48	0.86/0.60
HB1: Playing my favorite esports game has become a habit for me.	0.67	0.78
HB2: Playing my favorite esports game has become automatic to me.	0.65	0.83
HB3: If I have to select a task in my leisure time, it is an obvious choice for me to play my favorite esports game.	0.74	0.77
HB4: Playing my favorite esports game has become natural to me.	0.70	0.71
Price value (CR/AVE)	0.82/0.61	0.89/0.73
PV1: Playing my favorite esports game is reasonably priced.	0.71	0.80
PV2: Playing my favorite esports game is a good value for the money.	0.76	0.86
PV3: At this cost, my favorite esports game provides a good value.	0.86	0.90
Effort expectancy (CR/AVE)	0.82/0.54	0.88/0.65
EE1: Learning how to play my favorite esports game is easy for me.	0.75	0.86
EE2: My interaction with my favorite esports game is clear and understandable.	0.64	0.69
EE3: I find my favorite esports game easy to play.	0.78	0.84
EE4: It is easy for me to become skillful at playing my favorite esports game.	0.76	0.82
Social influence (CR/AVE)	0.88/0.71	0.90/0.75
SO1: People who are important to me think that I should play my favorite esports game.	0.88	0.90
SO2: People who influence my behavior think that I should play my favorite esports game.	0.78	0.83
SO3: People whose opinions that I value prefer that I play my favorite esports game.	0.87	0.86
Flow (CR/AVE)	0.87/0.69	0.93/0.82
FL1: I frequently experience flow when I play my favorite esports game.	0.82	0.91
FL2: In general, I have frequently experienced flow when playing my favorite esports game.	0.85	0.90
FL3: Most of the time, when I play my favorite esports game, I feel I am experiencing flow.	0.83	0.90
Esports gameplay intention (CR/AVE)	0.84/0.64	0.83/0.62
GI1: I plan to continue playing my favorite esports game frequently.	0.84	0.87
GI2: I intend to play my favorite esports game soon.	0.75	0.74
GI3: I expect to continue playing my favorite esports game in the near future.	0.81	0.75
Live esports streaming content		
LS1: Please state how many hours you have spent watching others esports gameplay, such as streamers' individual broadcasts in Twitch or YouTube Gaming per week.		

Notes: High frequency = High frequency of esports gameplay; Low frequency = Low frequency of esports gameplay.

3.3. Participants

The initial usable data were collected from 875 participants whose demographics were as follows: 66.2% men (*n* = 579), 33.8% women (*n* = 296); 68.8% ages 18–38 (*n* = 602), 22.2% ages 39–49 (*n* = 194); 28% household income of $4000–$69,999 (*n* = 245), 23.2% income of $70,000–$99,999 (*n* = 203). To create two groups by esports gameplay hours per week, one-third of the cases around the median were excluded [28]. The median time of weekly esports gameplay was five hours, so that 262 cases, approximately one-third of the initial 875, were excluded around the five-hour samples.

A total of 613 cases was retained, so that the distribution of the samples remaining approximated a bimodal distribution [29]. The cases of four hours, five hours, and six hours of gameplay were excluded. The mean number of esports weekly gameplay hours was 7.28. With respect to each group's gameplay time range, the low frequency esports gameplay (*n* = 309) ranged from one to four hours and the high frequency (*n* = 304) ranged from seven to 70 hours. According to Nielsen's report [30], the average number of esports fans' gameplay hours was approximately seven hours and the U.S. esports consumers'

demographics showed 75% men, 75% ages 18–34, with an average household income of $58,900.

In this study, the retained cases' (*N* = 613) average gameplay hours per week were 7.28 hours. With respect to their demographics, 70.8% were men (*n* = 389), 36.5% were women (*n* = 224); 70.8% were ages 18–38 (*n* = 434); 26.1% had household income of $10,000–$39,999 (*n* = 160), 29.5% had $40,000–$69,999 (*n* = 181), and 22.3% had $70,000–$99,999 (*n* = 137). Thus, the sample's features were consistent with esports consumers' demographic characteristics.

3.4. Data Analysis

The purpose of this study was to examine the effect of prior esports gameplay experience and gameplay time on the relationship between esports gameplay intention's antecedents and consequences. The groups with a high and low frequency of esports gameplay time were used in the moderation analysis. To examine the proposed research model (Figure 1), confirmatory factor analysis (CFA) and structural equation modeling (SEM) were conducted using SPSS v. 25 and AMOS v. 25, respectively. Bootstrapping was conducted to examine the indirect effects between the six determinants and live esports streaming content through esports gameplay intention. Specifically, 2000 resamplings were conducted with a bias-corrected 95% confidence interval to obtain an empirical distribution that was reasonably close to the true distribution.
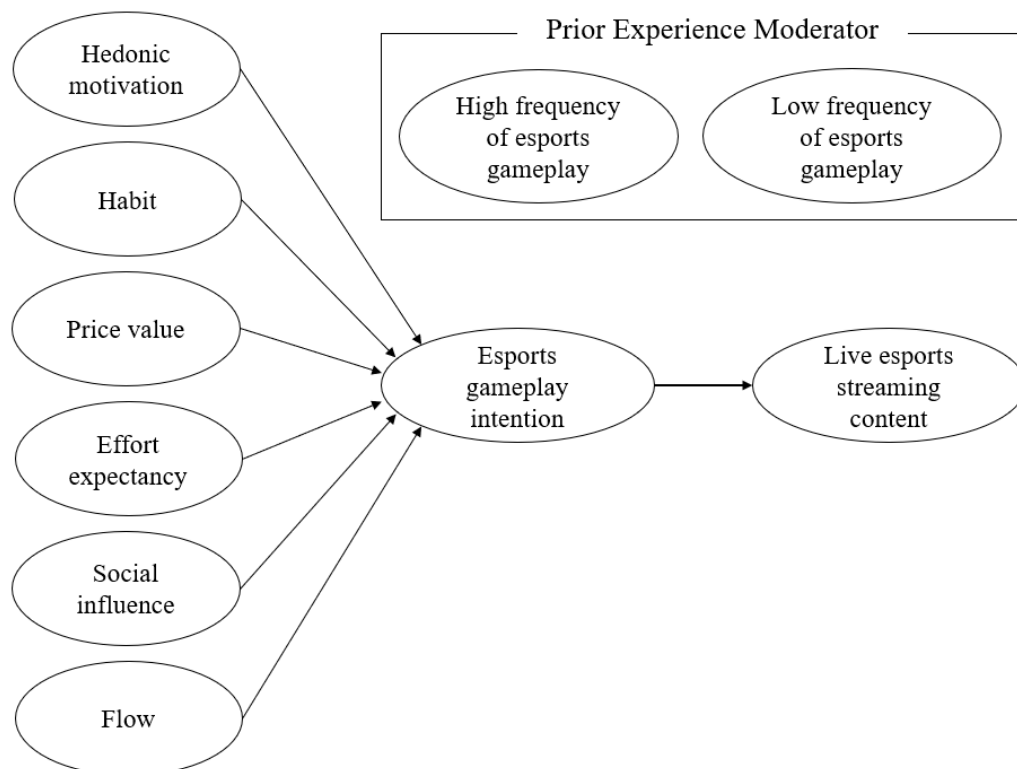

Figure 1. The Hypothesized Model.

4. Results

4.1. Assumption Tests

Assumption tests for CFA and SEM were conducted. The results of skewness (−1.31 to −0.19) and kurtosis (−0.36 to 3.02) indicated proper data normality based upon the criteria suggested [29]. The range in the variance inflation factor (VIF) (2.15 to 3.71) indicated that there was no multicollinearity issue with the data. Further, there were no outliers in the boxplot test results.

4.2. Measurement Model

A CFA was conducted to test the instrument's psychometric properties for both the high- and low-frequency groups of esports gameplay, and the model fit for both groups was found to be good (High frequency: χ^2 = 528.87, df = 225, $p < 0.05$; χ^2/df = 2.35; CFI = 0.92; RMSEA = 0.067; Low frequency: χ^2 = 594.141, df = 225, $p < 0.05$; χ^2/df = 2.641; CFI = 0.928; RMSEA = 0.073). The values of CR in the reliability test were above the suggested threshold of 0.70 [29]. Further, both groups' factor loadings were higher than the threshold of 0.50, which indicated acceptable convergent validity [29]. Specifically, the high gameplay frequency group ranged from 0.64 to 0.88, and the low frequency group from 0.69 to 0.91 (Table 1). The AVE values were higher than the squared correlations between variables [31]. In addition, all the correlations between the factors were below the threshold (<0.85) [5], which indicated acceptable discriminant validity (Table 2). The AVE value of the habit variable in the high frequency group was 0.48, which indicated insufficient variance in that variable. However, Hair et al. [29] stated that the AVE could be less than perfect (<0.50) when the mean values of items' factor loadings are less than 0.70, while the loadings are acceptable above the liberal threshold of 0.50. Given the lack of multicollinearity issues, the acceptable factor loadings (>0.50), and the variable's theoretical importance, the measurement model was retained.

Table 2. Correlations among All Variables.

High Frequency	AVE	1	2	3	4	5	6	7	8
1. Hedonic motivation	0.59	1							
2. Habit	0.48	0.67 * (0.44)	1						
3. Price value	0.61	0.53 * (0.28)	0.41 * (0.17)	1					
4. Effort expectancy	0.54	0.57 * (0.32)	0.61 * (0.37)	0.48 * (0.23)	1				
5. Social influence	0.71	0.33 * (0.11)	0.59 * (0.35)	0.27 * (0.07)	0.43 * (0.19)	1			
6. Flow	0.69	0.62 * (0.39)	0.70 * (0.47)	0.40 * (0.16)	0.71 * (0.51)	0.52 * (0.27)	1		
7. Gameplay	0.64	0.68 * (0.46)	0.73 * (0.53)	0.55 * (0.30)	0.60 * (0.36)	0.33 * (0.11)	0.59 * (0.35)	1	
8. Live-streaming	-	0.08 * (0.01)	0.28 * (0.08)	0.20 * (0.04)	0.07 * (0.00)	0.15 * (0.02)	0.16 * (0.02)	0.20 * (0.04)	1
Low frequency	AVE	1	2	3	4	5	6	7	8
1. Hedonic motivation	0.67	1							
2. Habit	0.60	0.83 * (0.69)	1						
3. Price value	0.73	0.39 * (0.15)	0.50 * (0.25)	1					
4. Effort expectancy	0.65	0.65 * (0.42)	0.69 * (0.47)	0.48 * (0.23)	1				
5. Social influence	0.75	0.06 * (0.00)	0.19 * (0.03)	0.35 * (0.12)	0.38 * (0.14)	1			
6. Flow	0.82	0.60 * (0.36)	0.63 * (0.39)	0.48 * (0.23)	0.74 * (0.54)	0.41 * (0.17)	1		
7. Gameplay	0.62	0.80 * (0.65)	0.79 * (0.63)	0.42 * (0.18)	0.58 * (0.33)	0.01 * (0.00)	0.54 * (0.29)	1	
8. Live-streaming	-	0.05 * (0.00)	0.20 * (0.04)	0.17 * (0.03)	0.02 * (0.00)	0.13 * (0.02)	0.16 * (0.03)	0.05 * (0.00)	1

*Notes: * $p < 0.05$; High frequency = High frequency of esports gameplay; Low frequency = Low frequency of esports gameplay; Gameplay = Esports gameplay intention; Live-streaming = Live esports streaming content.

4.3. Structural Equation Modeling

SEM was used to examine the paths in the proposed research model across the two groups. The model fits to the data were acceptable for both groups (High frequency: χ^2 = 552.97, df = 231, $p < 0.05$; χ^2/df = 2.39; CFI = 0.92; RMSEA = 0.068; Low frequency: χ^2 = 617.14, df = 231, $p < 0.05$; χ^2/df = 2.67; CFI = 0.92; RMSEA = 0.074). Table 3 presents the direct and indirect relationships in the research model. The structural analysis' results indicated three and four significant direct relationships across the high and low frequency groups, respectively (Table 3). Specifically, for the high frequency gameplay group, hedonic motivation (β = 0.39, $p < 0.05$), habit (β = 0.41, $p < 0.05$), and social influence (β = −0.17, $p < 0.05$) were found to have a significant direct effect on esports gameplay intention. For the low frequency gameplay group, hedonic motivation (β = 0.18, $p < 0.05$), habit (β = 0.53, $p < 0.05$), price value (β = 0.22, $p < 0.05$), and social influence (β = −0.16, $p < 0.05$) had a significant direct effect on esports gameplay intention. The direct relationship between esports gameplay intention and live esports streaming content was significant and positive (β = 0.21, $p < 0.05$) only in the low frequency gameplay group.

A bootstrapping technique was used to measure the indirect effect through esports gameplay intention. The range between the upper and lower limits of the 95% confidence interval should not contain zero, which indicated a nonsignificant effect [32]. The results showed that habit (β = −0.16, $p < 0.05$, 95% BC CI [0.049, 0.204]), price value (β = −0.16, $p < 0.05$, 95% BC CI [0.017, 093]), and social influence (β = −0.16, $p < 0.05$, 95% BC CI [−0.077, −0.006]) influenced live esports streaming content significantly and indirectly through esports gameplay intention only in the low frequency gameplay group. There was no indirect relationship in the high frequency gameplay group.

Table 3. Results of Structural Equation Modeling.

		High Frequency		Low Frequency	
Direct		β	*t*-Value	β	*t*-Value
Hedonic motivation	→ Gameplay	0.39*	3.10	0.18*	2.27
Habit	→ Gameplay	0.41*	2.97	0.53*	5.49
Price value	→ Gameplay	0.09	1.41	0.22*	3.73
Effort expectancy	→ Gameplay	0.03	0.26	0.12	1.53
Social influence	→ Gameplay	−0.17*	−2.85	−0.16*	−2.53
Flow	→ Gameplay	0.05	0.62	0.03	0.34
Gameplay	→ Live-streaming	0.07	1.18	0.21*	3.56
Indirect		*r*, [95% BC CI]		*r*, [95% BC CI]	
Hedonic motivation	→ Live-streaming	0.028, [−0.002, 0.095]		0.038, [−0.007 0.100]	
Habit	→ Live-streaming	0.029, [−0.005, 0.113]		0.113*, [0.049, 0.204]	
Price value	→ Live-streaming	0.006, [−0.002, 0.037]		0.047*, [0.017, 093]	
Effort expectancy	→ Live-streaming	0.002, [−0.015, 040]		0.025, [−0.010, 0.080]	
Social influence	→ Live-streaming	−0.012, [−0.043, 0.001]		−0.034*, [−0.077, −0.006]	
Flow	→ Live-streaming	0.004, [−0.008, 0.037]		0.006, [−0.033, 0.054]	

Notes: * $p < 0.05$; High frequency = High frequency of esports gameplay; Low frequency = Low frequency of esports gameplay; Gameplay = Esports gameplay intention; Live-streaming = Live esports streaming content; 95% BC CI = 95% Bias-corrected confidence intervals.

4.4. Conclusions

The high-frequency and low-frequency groups were appropriately divided. The assumption test and model fit were suitable to test SEM. According to the SEM results, in the high-frequency group, esports gameplay did not affect their engagement in live esports streaming content for consumers. Hedonic motivation, habit, and social influence were significantly associated with the esports gameplay intention. However, in the low-frequency group, gameplay intention successfully predicted live esports streaming content engagement. The four drivers (hedonic motivation, habit, price value, and social influence) were found to predict esports gameplay intention.

5. Discussion

The purpose of this study was to explore the effects of prior esports gameplay experience using gameplay time and examining its effect on the relationship between esports gameplay intention's antecedents and consequences in the ESC model. The group with lower esports gameplay time (prior experience) was distinguished from the group with higher esports gameplay time depending upon their gameplay time. The results supported the hypothesis, as the two groups showed different patterns based upon the frequency of their prior gameplay experience. Jang and Byon [3] examined the ESC model with general esports gameplay consumers and found a significant and positive relation between esports gameplay and esports media consumption. Jang et al. [4] divided esports

media consumption into two separate types of consumption: Streamers' live esports streaming content and esports event broadcasts, and found direct, significant effects of esports gameplay intention and live esports streaming content.

Based upon the findings of previous studies, the lack of a significant direct relationship between esports gameplay intention and live esports streaming content in this study was surprising. This is because individuals who invest much effort and spend a great deal of time in gameplay are likely to be considered avid gaming consumers (i.e., hardcore gamers) [17]. Still, the results indicated that esports gameplay had no effect on the consumption of live esports streaming content among esports consumers who have more experience and more gameplay time. In contrast, in the group with less gameplay experience, esports gameplay intention predicted live esports streaming content consumption successfully. It may be understandable that some esports consumers who have more esports gameplay experience tend to be eager to play esports games, yet they may not prefer to watch others' esports gameplay. According to the gamer types in Newzoo's report [33], "conventional gamers" have much gaming equipment and great enthusiasm for gameplay, but they prefer to watch other's gameplay less. Another type of gamer, the "backseat viewers," like to play their esports games, but they cannot play as much as they did before because they are older and have other responsibilities. Thus, they watch others' gameplay only when they have time to spare [33]. To examine prior experience and market segmentation, future research may need to consider both types of esports consumption.

Other different patterns across the two groups were the relationship between price value and esports gameplay intention. Although highly experienced esports consumers may consider it a pleasure to engage in gameplay (hedonic motivation) and play continuously (habit), less experienced esports consumers may count on price value as much as habit and the joy of gameplay. The price value is the monetary cost to play esports games. Consider the "Freemium" business models [34], in which the basic functions of gameplay are provided free of charge and then a monetary cost is charged for the full gameplay experience. This may explain price value's significance in the low frequency group. The in-game items usually attract gameplay consumers because the gameplay is convenient [35]. For example, some of the popular in-game items are the "boost" items that save game users time and effort in reaching the in-game achievements. Because individuals who have little esports gameplay experience may need to save their time, they may consider the price value for their gameplay. Future researchers may need to focus on the in-game item purchasing consumption in the esports context.

Esports consumers' age and stigma may explain social influence's negative, significant effects on esports gameplay intention. The negative relationship between social influence and gameplay intention may be explained as gamers' desire to play their favorite esports game, although the social environment does not support it. The U.S. esports consumers' demographics showed that 75% were 18–34 years of age [30], which may indicate that esports gameplay consumers have a spouse, significant other, or child. As esports gaming has been often stigmatized as a gaming addiction [36], the negative relation may be explained as the social environment's discouragement of gameplay, and the challenge may motivate and ignite a desire for esports gameplay.

5.1. Theoretical Implications

With respect to theoretical implications, the findings contributed to (1) esports research by supporting the esports consumers' heterogeneity, (2) the extension of the technology acceptance and use model to esports consumers' behaviors by identifying prior experience effects. Although esports consumers are heterogeneous, only a few studies have explored esports consumer segmentation [12,13]. In video game research, gamers have been categorized as "hardcore gamers" and "casual gamers" based upon their gameplay frequency [16,17]. However, in the esports context, gameplay time has not received significant attention to date. Thus, this study provided empirical evidence that

esports gameplay time can be used to segment esports consumers. Another theoretical contribution was that this study focused on prior experience in esports consumer behavior. Because the esports industry is related closely to technology use, the technology acceptance and use approach may help explain esports consumers' behaviors [3]. Technology acceptance research has considered that prior experience predicts both behavioral intentions and actual behaviors [14,19,20]. Thus, the findings of this study explained esports consumers' behaviors better by considering prior gameplay experience. Broadly, identifying prior experience may extend the ESC model, which is based upon the unified theory of technology's acceptance and use.

5.2. Practical Implications

With respect to the practical implications, the findings indicated that low frequency gamers may attract more attention from practitioners. In the aspect of the consumption chain between esports gameplay and live esports streaming content, the esports gameplay group with less experience may need to be considered more valuable consumers than those who have greater experience. This may be interesting because gamers who spend time and effort on gameplay are likely to be considered avid gaming consumers [17]. For example, while the mobile game market and esports leagues have been growing quickly, many professionals in the gaming industry have predicted that the hardcore gaming crowd may not prefer to play mobile games [37]. As such, hardcore gamers have been often considered primary consumers. However, the stereotype may have changed recently because esports gaming also includes watching others' gameplay. For example, according to D'Anastasio [38], Twitch fostered the unique culture of hardcore gamers watching their peers' gameplay, so that Twitch viewers were considered widely to be unwelcoming to casual gamers. D'Anastasio [38] indicated that the culture has changed over time, and there is a need for casual contents in gameplay, such as more communication with streamers or listening to the streamers' talking with friends as well as music. As another example, the results indicated that streamers may challenge new esports games to target the casual gamers. If the streamer is a novice at an esports game, this might be even better for the viewers. Payne et al. [39] indicated that esports content viewers have more positive perceptions of novice streamers in the aspect of learning gameplay strategies than streamers who have achieved a professional level of gameplay. Thus, the instructional content for casual gamers may be appropriate for their level. Since casual gamers are the target viewers, a schedule for live streaming may need to be considered for the viewers' characteristics, such as evenings, weekends, and comparatively shorter sessions. On the other hand, hardcore gamers may be more interested in playing their favorite esports games rather than watching streamers' live streaming content. Not surprising, hardcore gamers are attracting consumers for the esports game developers' companies and gaming gear firms. While this study did not test this fact, we can speculate that hardcore gamers might prefer to watch professional gamers' performance in institutionalized esports tournaments. Since hardcore gamers spend tremendous time and effort on increasing their gaming skills, they might not be satisfied with the performance of the streamers. Although former professional esports players usually become streamers after they retire, their performance is typically less than those of the current pro-gamers. Moreover, some successful streamers are not former professional esports players. Future studies may be needed to examine the gamer clusters to determine the relationship between gameplay consumption and watching broadcasts of esports events.

This study's findings are consistent with this known phenomenon. For esports consumers who play infrequently, marketing strategies that target the connection between gameplay and watching live esports streaming content may be more effective than for consumers who play esports games frequently. For example, when promoting esports games with recently updated in-game content, offering emoticon items that provide live-streaming chatting as participation gifts may attract gameplay consumers

who play esports games infrequently. As such, esports game marketers may create more tailored strategies for their consumers.

5.3. Limitations and Suggestions for Future Study

This study has certain limitations. First, the coefficient between esports gameplay intention and the actual behavior of live esports streaming content had a relatively lower magnitude. Although social psychological theories have shown that intention is generally a good predictor of actual behavior [14], this low conversion from intention to behavior needs to be acknowledged. A possible cause may be potential barriers between intention and behavior. Specifically, there may be unexpected situations, such as lack of money or time when consumers wish to engage in the behavior [14]. With that said, future researchers should consider incorporating perceived behavioral control defined as the perception of how easy or difficult it is to perform the behavior of interest into the tested model in this study.

Second, while this study identified prior experience with esports gameplay based upon gameplay time and different patterns in the paths across the two groups, the groups' differences and similarities were not compared statistically. Future studies may need to explore prior esports experience and examine the groups' comparisons. According to the growth of esports, gameplay consumers' experience has become diverse because it includes multiple different forms of esports consumption, such as gameplay, watching others' gameplay, purchasing for gameplay, and attending esports events [3–5]. This may require further investigation of prior esports experience other than esports gameplay. For example, the gamer types in Newzoo's report [33] suggested eight different characteristics of esports consumers. Future research should consider additional elements, such as esports media consumption, to explain esports gameplay consumers' prior experience better.

Lastly, while the findings of this study revealed the factors and clusters that impact esports consumers' engagement in gameplay, other valuable elements may need to be considered by future studies. For example, most esports games have a ranking system for the competitive setting. Although it is an esports game, consumers might have different perceptions for playing the normal games (i.e., those with no influence on the ranking system) and the ranking games, especially for the promotional games in the ranking system. As another example, emerging technology, such as virtual reality, might extend the area of esports game gear. As speculation, if virtual reality gear (e.g., *Oculus Quest*) was adopted in the esports games, it might significantly influence consumers' various perceptions of technology acceptance and players' motor and psychological skills.

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