Analysis of Break in Presence During Game Play Using a Linear Mixed Model

Jaeyong Chung, Hwan-Jin Yoon, and Henry J. Gardner

Breaks in presence (BIP) are those moments during virtual environment (VE) exposure in which participants become aware of their real world setting and their sense of presence in the VE becomes disrupted. In this study, we investigate participants' experience when they encounter technical anomalies during game play. We induced four technical anomalies and compared the BIP responses of a navigation mode game to that of a combat mode game. In our analysis, we applied a linear mixed model (LMM) and compared the results with those of a conventional regression model. Results indicate that participants felt varied levels of impact and recovery when experiencing the various technical anomalies. The impact of BIPs was clearly affected by the game mode, whereas recovery appears to be independent of game mode. The results obtained using the LMM did not differ significantly from those obtained using the general regression model; however, it was shown that treatment effects could be improved by consideration of random effects in the regression model.

Keywords: Presence, computer game, breaks in presence (BIP), linear mixed model (LMM).

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I. Introduction

Recent technological advances have initiated an important transformation in the video game industry. Modern video games are no longer just a screen and joypad form of entertainment. Rather, they involve complex physical and/or psychological interactive experiences, often involving multiple gamers. Designing a game to be an enjoyable entertainment experience is the ultimate goal of game developers [1].

In particular, games that produce a heightened sense of presence or the feeling of "being there" in an artificial world are expected to be highly entertaining [2]. Such a high level of interest from the video game industry has also motivated us to determine which design variables in games might enhance the virtual presence of game players during play.

1. Presence and Breaks in Presence

Presence is commonly defined as "the subjective feeling of being there" and "the perceptual illusion of non-mediation" [3]. Numerous studies have examined the effects of several factors on the feeling of presence [4]-[12]. Some of the factors that are known to affect this feeling are the frame rate, field of view, sound, latency, control, proprioception, and real-world distractions.

During game play, a gamer is likely to meet various types of unexpected impediments. These distractions are known to degrade the feeling of presence experienced by a player. As a more quantitative method of analyzing the presence of the player, Slater and others [13] introduced the concept of a break in presence (BIP). The concept of BIP indicates the level of perception of participants simultaneously from the real and virtual worlds, and the manner in which this perception affects their response to the real world to a higher level than to the virtual world. To estimate the subjective feeling of presence using this concept, participants were asked to provide a signal each time that a BIP occurred. Further, the researchers examined the association between a BIP and the player's physiological responses [14]. In a companion paper based on a qualitative analysis of interviews, it was suggested that BIPs have multiple causes and various intensities, resulting in various recovery times [15]. It was also argued that participants have to make an effort to recover from a BIP, and in some cases, they required greater effort to feel the presence again. However, it was not possible to obtain a quantitative understanding of this variation in presence after BIPs.

Based on such previous studies, we conducted a user study in which we investigated how participants experience (from the point of view of presence) technical anomalies during game play. We varied the type of BIP using four effects and quantitatively measured the variation in presence using a questionnaire. In addition, we compared the BIP responses in two game modes: a navigation mode (non-violent) and a combat mode (violent). Numerous studies have suggested that game violence is significantly associated with the subjective feeling of presence [16]-[18].

Ijsselsteijn and others found that participants used remarkably different scales in their presence ratings [19]. The common method used to exclude the effect of this individual variation is the *z-score transformation*, which converts each participant's absolute score into a z-score, which indicates the deviation from the mean value in standard deviation unit [20]. To normalize for individual differences in scale, Ijsselsteijn and others applied the z-score transformation to their experimental data [19]. Dijk and others also adopted the z-score transformation in their study because some of their subjects did not use the full range of the numerical scale in their assessment [21]. However, there was a limitation when using the z-score transformation in a nested model that removed a "main effect." For instance, because there were two game categories as well as BIP effects within each game mode, it was only possible to test the BIP effect and not the effect of the game mode.

In this paper, we introduce a linear mixed model (LMM), and compare the results obtained using this model with those obtained using a conventional regression analysis (RA) to investigate how individual differences could affect the outcome.

II. Statistical Analysis Using Mixed Model

Several presence-related studies have applied linear RA to their experimental results [9], [11], [22], [23]. Basically, RA seeks to account for the variation in a response variable by relating it to one or more explanatory variables, whereas analysis of variance (ANOVA) seeks to detect variation among the mean values of groups of observations. In RA, the statistical significance of each explanatory variable is tested using the same estimate of residual variance, and this estimate is also used to calculate the standard error of the effect of each explanatory variable. However, this choice is not always appropriate. Sometimes, one or more terms in the regression model represent random variation, and such terms will contribute to the variation observed in other terms. It should therefore contribute to the significance tests and standard errors of these terms, but in an ordinary RA, it does not do so. Using ANOVA, on the other hand, does allow the construction of models with additional random-effect terms, known as block terms; however, it does so only in the limited context of balanced experimental designs.

A mixed model [24] allows the presence of additional random-effect terms to be recognized in the full range of regression models, not just in balanced designs. Any statistical analysis that can be specified by a general linear model or ANOVA can also be specified by a mixed model. However, the specification of a mixed model requires an additional step. For each term in the model, the researcher must determine whether the effects of that term can be regarded as a random sample from a much larger population or whether they are a fixed set. Provided that an appropriate decision is made, a mixed model specifies a statistical analysis that has broader validity than RA or ANOVA, and which is nearly equivalent to those methods in the special cases where they are applicable.

Let us consider a conventional regression model, which can be written as

$$y = \text{Game\_mode} + \text{BIP} + \text{Game\_mode} \times \text{BIP} + \varepsilon, \quad (1)$$

where $\varepsilon \sim N(0, \sigma^2)$.

Since our data structure is nested, the LMM is given as

$$\begin{aligned} y = \ & \text{Game\_mode} + \text{BIP} + \text{Game\_mode} \times \text{BIP} \\ & + \text{subject} + \text{Game\_mode} \mid \text{subject} + \varepsilon, \end{aligned} \quad (2)$$

$$\text{where} \begin{cases} \text{Game\_mode|subject} \sim N(0, \sigma^2_{\text{GM|subject}}), \\ \text{subject} \sim N(0, \sigma^2_{\text{subject}}), \\ \varepsilon \sim N(0, \sigma^2). \end{cases}$$

Subject (participant) and the game mode nested in Subjects (Game mode | subject) are regarded as random effects in this study.

III. Methods

Participants included 36 undergraduate and postgraduate

Fig. 1. View of VR theatre.

Fig. 2. Screen shot of combat mode session.

students with a mean age of 22 years (SD=2.9). All participants reported playing computer games at least once a month. Each participant received a movie ticket for their participation and was recruited through advertisement around the university campus. The university's human ethics committee approved this study, and all participants were instructed in accordance with the committee's ethical guidelines.

The experiment was conducted in a virtual reality (VR) theatre with two, rear-projected, 2.9 m × 2.2 m screens. The screens were joined at an angle of 90°, providing an almost 180° degree immersive field of view (see Fig. 1). The VR theatre was isolated during the experiment. We had full control over the ambient lighting and sound in this setting as well as the other programmable aspects of the virtual environment (VE). Even though its stereoscopic and head-tracking capabilities were not used, the large-display 3D graphics functionality was expected to increase the feeling of presence relative to playing games in a normal desktop setting.

1. Game Environment

In general, a first-person shooter (FPS) game requires intensive interaction of the participants, incorporating tasks such as shooting, aiming, moving around, and so on. For this research, we adopt an FPS game which was originally implemented to test a commercial 3D game engine [25]. We ported this game to our immersive two-screen display and modified the game in order to implement two different game modes (navigation and combat) for our research.

In navigation mode, there was no particular mission or threat of attack. Participants were asked to explore the environment, which was the interior of a two-story building including a grand staircase and balcony, all with medieval decor. Players had use of their weapon in this mode, and they could amuse themselves by taking shots at stationary enemy avatars which were scattered through the building, and would not retaliate.

On the other hand, in combat mode, participants were subject to continuous attack by enemies and they therefore needed to engage in typical FPS tactics, such as moving quickly, shooting, hiding, and so on. The enemy avatars were under the control of a remote participant who was an experienced player of this game level and who tuned the intensity of their attack to be always just at, or above, the level of competence of the subject.

2. BIP Design

To investigate participants' subjective feeling of BIP during game play, we designed four induced technical anomalies described in Table 1.

BIP 1 (low frame rate) frequently occurs during the course of real game play. The frame rate suddenly degrades to 5 fps when BIP 1 is triggered. When BIP 2 (sound absence) occurs, any and all game sound effects totally disappear. Concerning BIP 3, participants' interaction commands, especially mouse events for view control and keyboard events for translating, are inverted. When BIP 4 is triggered, as in [14], the screen

Table 1. BIP effects used in the experiment.

	Description
BIP 1 (low frame rate)	Degrade to 5 fps
BIP 2 (sound absence)	Sudden absence
BIP 3 (reverse control)	Mouse and keyboard events (for navigation) were inverted
BIP 4 (black out)	Screen turned totally black

becomes totally black (equivalent to turning off the screen).

In our experiment, each BIP effect lasted for 3 s to 4 s and was triggered periodically at set intervals (60 s). However, we considered other factors that might influence our evaluation of the effect of anomalies. For example, each BIP effect was not triggered in combat mode unless an enemy was located within the participant's viewing frustum. We assumed, for example, that the effects of BIPs might have a more intensive impact on presence when participants were aggressively fighting with an adjacent enemy, as compared to a situation where participants were simply moving to another location to look out the window. In addition, with BIP 3 (reverse control), the effect was not triggered unless a participants' mouse or keyboard was active at the time. As a result, the actual BIP triggering times were different for each participant, though not markedly so, due to the continuous nature of engagement.

3. Procedure

Two groups formed randomly each with 18 participants played both game modes but in the opposite order. At the beginning, each participant received an information sheet detailing the procedure of the experiment and a brief overview of the equipment used, followed by a simple questionnaire related to their background, including age, game experience, tendency to motion sickness, and so on. This information sheet was designed primarily to familiarize participants with the concepts of presence and BIP. In addition, we explained to the participants that the game that they were about to play was not a complete version; thus, technical problems could occur at any time. This was done to reduce the irregular and/or severe impact of unexpected technical anomalies on participants at the first instance. This ensured that the collected data was more normalized. However, there were several unnatural factors such as collision-detection errors, texture errors, and so on.

Before the actual game experiment session, the participants had a training period of around four minutes to get accustomed to the immersive VE, interaction technique (keyboard/mouse), and game control (see Fig. 3). This procedure, a so-called gradual transition from real world to virtual world, has been shown to increase the participant's sense of presence in the actual experimental session [26].

The actual experimental session lasted for six minutes. After playing the game in each mode, all of the participants were asked to complete a simple, post-experiment survey. The first two questions were the following Likert-scale questions concerning the perceived impact and recovery from each BIP:

Q1. Were there any moments when you suddenly became aware of the VR theatre area? (Some people call these events BIP) If you can remember them, describe what triggered these moments, and rate each of them with their impact on your feeling of presence. (Use ratings of 1 for no impact, to 4 for moderate impact, to 7 for very strong impact.)

Fig. 3. Screen shot of the training session.

Q2. For each of the items you listed in question 1, how much time was needed for you to feel very involved in the game environment after these events? (Use ratings of 1 for very quick, to 4 for moderate, to 7 for a very long time.)

IV. Results

The navigation group played the game in the navigation mode first and the combat mode second, while the combat group played the game in the combat mode first and the navigation mode second. Therefore, the experimental results were divided into four categories: navigation first (NF), combat first (CF), navigation second (NS), and combat second (CS), based on the game mode and its order. Two response variables were considered in this study, impact and recovery. The independent variables were the game modes (NF, CF, NS, and CS) and BIP factors (BIP 1, BIP 2, BIP 3, and BIP 4).

1. Impact

For fixed effects, both the conventional RA and LMM showed that there were statistically significant main effects of the game modes (Wald statistics: (11.80, 10.83), p-value: (0.008, 0.013)) and BIPs (Wald statistics: (32.18, 39.52), p-value: (<0.001, <0.001)). These results indicate that participants felt different levels of impact from different sorts of technical anomalies and that the level of impact was significantly affected by the game mode. Moreover, there was a significant interaction effect between the game modes and BIPs (Wald statistics: (18.89, 23.20), p-value: (0.026, 0.006)). Table 2 lists the comparison between the general regression and LMM analyses.

Table 2. Comparison between RA and LMM (impact).

Term	Method of analysis					
	General RA			Mixed-model analysis		
	Wald statistics	df	p-value	Wald statistics	df	p-value
Fixed effect						
GM	11.80	3	0.008	10.83	3	0.013
BIP	32.18	3	<0.001	39.52	3	<0.001
GM×BIP	18.89	9	0.026	23.20	9	0.006
Random effect						
Subject				$\sigma^2_{\text{Subject}} = 0.449\ (0.193)$		
GM within subject				$\sigma^2_{\text{GM\|Subject}} = 0.051\ (0.151)$		

Note. GM: game modes, BIP: break in presence, df: degree of freedom.

Table 3. LRT for impact.

Model	Deviance	df	p-value
RA	576.56	269	–
LMM	557.07	267	–
RA vs. LMM	19.47	2	<0.001

For random effects, the variance-component estimate for the term "subject (participant)" (0.449) is larger than its standard error (0.193), which suggests that there is a real natural variation among participants. The variance-component estimate for the game modes (GM) within a participant (0.051) is smaller than its standard error (0.151), suggesting that the natural variation between game modes within a participant may be no greater than that of the subject.

As shown in Table 2, the GM effect in RA was overestimated by the effect of individual variation. Therefore, the BIP effect and interaction effect were slightly underestimated, whereas the LMM showed that the BIP effect and interaction effect were improved by considering individual variation.

We also conducted a likelihood ratio test (LRT) which is used to compare the fit of two models one of which is nested within the other [27]. Table 3 shows the LRT results for the model comparison.

The chi-square test statistic of 19.47 with 2 degrees of freedom gives a p-value of <0.001, indicating that the LMM is a better model than RA.

2. Recovery

Both methods, RA and the LMM, showed that BIP had

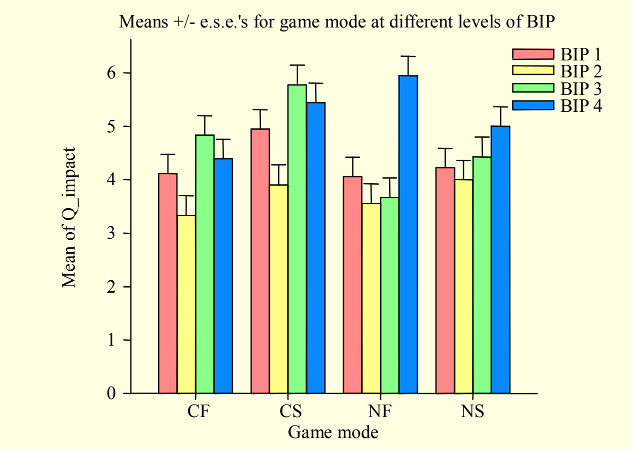

Fig. 4. Mixed model analysis impact results.

significant effects (Wald statistics: (21.91, 27.53), p-value: (<0.001, <0.001), respectively). However, unlike impact, there was no major effect related to game mode and no interaction effect between game modes. That is, recovery seems to depend on the type of BIP but seems to be independent of the game type.

In the LMM, the variance-component estimate for the term "subject (participant)" (0.605) is larger than its standard errors (0.208), which suggests that there is a real natural variation among participants. The variance-component estimate for the game modes within a participant showed no variation (0.000).

As shown in Table 4, the GM effect in RA was overestimated by the effect of individual variation; therefore, the BIP effect and interaction effect were slightly underestimated. On the other hand, in the LMM, it was seen that the BIP effect and the interaction effect were improved by considering individual variation. Table 5 shows the results for the model comparison.

The chi-square test statistic of 30.23 with 2 degrees of

Table 4. Comparison between RA and the LMM (recovery).

Term	Method of analysis					
	General RA			Mixed-model analysis		
	Wald statistics	df	p-value	Wald statistics	df	p-value
Fixed effect						
GM	1.74	3	0.627	1.20	3	0.753
BIP	21.91	3	<0.001	27.53	3	<0.001
GM×BIP	4.58	9	0.869	5.43	9	0.795
Random effect						
Subject				$\sigma^2_{\text{Subject}} = 0.605\ (0.208)$		
GM within subject				$\sigma^2_{\text{GM\|Subject}} = 0.000$		

Note. GM: game modes, BIP: break in presence, df: degree of freedom.

Table 5. LRT for recovery.

Model	Deviance	df	p-value
RA	570.58	269	–
LMM	540.35	267	–
RA vs. LMM	30.23	2	<0.001

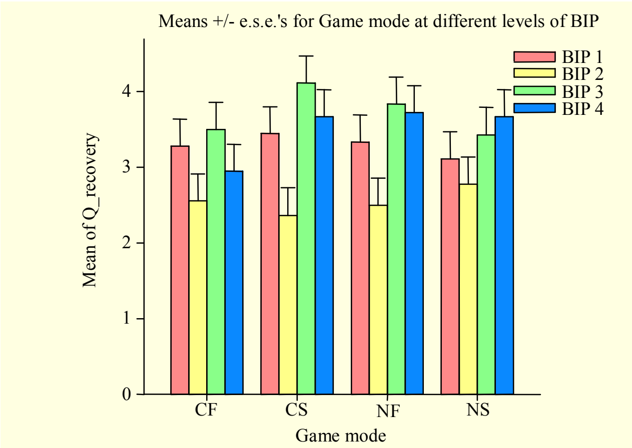

Fig. 5. Mixed model analysis recovery results.

freedom gives a p-value of <0.001, which indicates that the LMM is a better model than RA.

V. Discussion

In mixed-models, random factors are treated in a more complicated way. While we are interested in the total variation in outcomes attributable to the random factor (its variance), we might also be interested in specific levels of random factors. For instance, in looking at differences between individuals in a treatment group (combat) and a control group (navigation), we might measure each individual a number of times. Some individuals will consistently score higher than others for reasons other than whether they were in the treatment group or not. In testing whether there is any difference for a fixed effect between the treatment group and the control group, we might want to control the random effect of individual differences. That is, we want to exclude this individual level variance from the outcome when testing for a treatment effect.

As shown in Tables 2 and 4, when individual level variance was taken into account, the LMM showed the treatment effect more clearly than RA. With balanced data, random factors do not cause inference problems for tests of fixed effects. Furthermore, an LRT showed that the LMM was a better model than RA. However, with unbalanced data, it is possible to mistakenly infer treatment effects.

In this paper, we demonstrated the application of the LMM using impact and recovery data obtained by a questionnaire, even though the results of both a conventional regression model and those of an LMM did not differ much in term of the significance (p-value). However, we could still identify differences between the two methods. The LMM could improve the test statistics. The data used in this study was well balanced, and the individual differences in this data were confined within a certain range; therefore, the results from both methods were similar. In the LMM, we treated the subject variable as a random effect. That is, we regarded the effects of the subject variable as a random sample of the effects of all participants. As shown in Tables 2 and 4, by considering random effects in the regression model, the treatment effects could be improved. In addition, the LRT test for model comparison showed that with regard to the results of impact and recovery, the LMM was a better model than RA.

The results obtained using both methods indicate that induced technical anomalies were experienced as BIP by participants and that fluctuation in presence varied in terms of the degree of impact and recovery. The impact and recovery results differed significantly, depending on the type of technical anomaly. Interestingly, the impact of a BIP was significantly influenced by perceived violence, while recovery appears to be independent of game type (violent/non-violent) and game order (first experience/second experience). Furthermore, game mode was found to produce a significant effect in the measurement of impact, but not in the measurement of recovery.

Interestingly, contrary to our expectation, impact and recovery exhibited quantitatively different characteristics, in that they appear somewhat independent of one another. In other words, a bigger impact does not necessarily provoke a longer duration of recovery. Moreover, recovery time appears to only depend on the type of BIP experienced.

VI. Conclusion

We investigated participants' experience when they encounter technical anomalies during game play. We then compared the effects of violent and non-violent games on their experience, using a LMM and a conventional regression model.

There were some limitations in our experiment. Most of all, the level setting and the duration of the BIP effects were set arbitrarily, even though we considered previous similar studies. Therefore, our results cannot be used as a benchmark for each BIP type. That said, this is not the purpose of our study. However, this experiment might be improved by designing each item to incorporate more than two levels.

Video games are becoming more technologically advanced, and are increasingly realistic and engaging, expanding in both genre and platform. Considering today's fast-paced game technology, it is expected that undesirable factors impeding gamers' feeling of presence in play may increase or diversify over time. Thus far, even some commercial games have strategically incorporated a number of negative technical effects to increase in-game amusement.

Future experiments will attempt to provide more substantial evidence and analyze the tentative results described here as well as examine the effects of some other forms of BIP events noted by the participants in this study. We believe that combining sophisticated statistical analysis with a presence-related study may contribute to the design of a more enjoyable game experience in the future.

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