The Linguistic Environments of Digital Games: A Discriminant Analysis of Language Use in Game Mechanics

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The linguistic environments of digital games: A discriminant analysis of language use in game mechanics

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Abstract  
This study quantitatively measures the variation in language derived from a targeted set of digital game mechanics. Mechanics refer to the design elements of a game that make up the overall gameplay experience, determining player actions and the degree of language interaction. A corpus was compiled by extracting the language files of two popular commercial games, Fallout 4 and Skyrim, using “modification” software. The extracted language files were organized into three register categories following the register framework in Biber and Conrad (2019). The three categories include one spoken (dialogue trees) and two written registers (quest objectives and quest stages), which are common mechanics in many modern commercial games. Comparing results from three discriminant analyses, findings indicate that statistical models cannot distinguish between the two games’ linguistic environments at the level of the game; however, when considering the linguistic environments at the level of game mechanic, the model has high precision in accurately identifying the texts’ game mechanic register category. The results give empirical evidence that DGBLL research designs could benefit from targeting specific design aspects and game mechanics rather than generalizing results at the level of genre or game title.

Keywords: digital game-based language learning; corpus linguistics; discriminant analysis; game mechanics; open world games
Introduction

While digital game-based language learning (DGBLL) has continued to receive much attention in second language (L2) research, findings may have limited generalizability. Generalizability concerns were raised several years ago when Cornillie, Thorne, and Desmet (2012) stressed the need for a “game element” approach to DGBLL research that aims “to identify and define the formal constituents of games” (p. 245). More recently, Reinhardt (2019) described these elements or game mechanics as “key to designing and researching gameful second language teaching and learning, because mechanics can be associated directly to potentials for L2 learning” (p. 94). However, DGBLL research has tended to focus on game genres or a game as a whole. The issue raised with these approaches is that even a small difference in a design or mechanic “can make all the difference in what behaviors are made possible” (Reinhardt, 2019, p. 97). DGBLL research that considers game mechanics and the linguistic environments within these mechanics can provide much needed precision and insight into the specific aspects that make a digital game more or less effective for L2 learning, a call for research echoed by Vandercruysse et al. (2013) and Reinhardt (2021). However, before the L2 learning effectiveness of targeted mechanics can be measured, it is first important to identify and investigate the linguistic environments derived from game mechanics along with the variation that makes each mechanic linguistically unique, which is the primary aim of the current study.

Without extensive gaming experience, identifying game designs and mechanics can be challenging. Reinhardt (2019) explains “a game mechanic is a programmed action in a game that a player can follow to reach a goal” and determines what a player can or cannot do during gameplay (p. 94). These mechanics serve a variety of communicative purposes in specific contexts, giving a sense of agency to the players as they make choices in the vast interactive virtual worlds of digital games. Such choices affect the games’ storylines, narratives, and the relationships with its many automated characters. Various designs and mechanics can also affect the degree of language interaction required during gameplay. The importance of understanding a game’s design in L2 contexts is highlighted in deHaan et al.’s (2010) study that compared the L2 vocabulary gains from L2 learners playing a game, PaRappa the Rapper 2 (NanaOn-Sha, 2001), versus a control group that simply watched others play the game. Participants playing the game recalled significantly less vocabulary items than did participants watching the game. They concluded that “interactivity hindered the language acquisition process” and noted that attention to L2 input was not crucial for success in this particular game (p. 85). That is, to progress in the game, players only need to press the right button at the right time, and the language input could be largely ignored. This shows the importance of understanding a game’s design because various mechanics may or may not require attention to language input in order to complete the designed goals and objectives of any particular game.

Applying the register framework to game mechanics

From a linguistic perspective, game mechanics might be better understood using the register analysis framework detailed in Biber and Conrad (2019). They use register to refer to a language
“variety associated with a particular situation of use” (p. 6). That is, certain linguistic forms are more or less common in one register compared to another because these forms serve functions within the registers’ unique situational contexts. For example, in the general register of spoken conversation, Biber and Conrad frame the situational contexts to include real-time production and a shared time and space. These interactive characteristics of conversation tend to include higher frequencies of pronouns, contractions, and vague references, among other features when compared to registers outside of conversation (i.e. written registers).

Drawing on this register perspective, the language derived from game mechanics can be considered unique registers because they are designed to serve unique communicative purposes within the games’ various situational contexts and goals. The three game mechanics targeted in this study are referred to as dialogue trees, quest objectives, and quest stages. Table 1 outlines these mechanics as register categories, listing their unique communicative purposes. For readers with limited gaming backgrounds, some common gaming terminology is first defined:

- **The Player** refers to the real-life person playing the game and, in this study, the pronoun they is used to refer to the Player since gaming is obviously not limited to any one gender.
- **The Player’s Character** refers to the avatar that represents the Player in the game’s virtual world.
- **Non-player’s characters** (NPCs) refer to the automated characters in games that are programmed to react based on the Player’s choices.
- **Quests** refer to the tasks or objectives that the Player completes to progress in the game, often in stages and increasing in difficulty.

<table>
<thead>
<tr>
<th>Game mechanic register</th>
<th>Communicative purposes(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dialogue Trees (spoken)</td>
<td>▪ Provides the Player with dynamic interactive dialogue options that affect the game’s story and relationships with NPCs</td>
</tr>
<tr>
<td></td>
<td>▪ Provides critical information for completing quests</td>
</tr>
<tr>
<td></td>
<td>▪ Adds a sense of immersion and scale to the virtual worlds of games</td>
</tr>
<tr>
<td>Quest Objectives (written)</td>
<td>▪ Provides a concise list of the actions that need to be taken to complete a quest</td>
</tr>
<tr>
<td>Quest Stages (written)</td>
<td>▪ Provides a narrative summarizing the story and purposes behind the quest objectives and is usually written from the perspective of the Player’s Character in first-person</td>
</tr>
</tbody>
</table>

This framework includes one spoken register, *dialogue trees*, and two written registers, *quest objectives* and *quest stages*. While there are a number of game mechanics that are not
included here, the three targeted mechanics are quite common in many modern games, and thus deemed to be a productive starting place for developing a digital game mechanic register framework. However, this framework is intended for a specific target population of games to which this study aims to generalize results. Targeting all digital games in a single framework would not be possible due to the large variety of designs. Before detailing each mechanic register category, it is first important to describe the target population of games, how they are played, and justification for their use in this study. This discussion is followed by details of how the targeted game mechanics are presented in these games, and screenshots are used to illustrate their use of these mechanics.

The target population of games, how they are played, and their extensive use of language

This study seeks to quantitatively measure the variation within the language used in three game mechanics as they are presented across two popular commercial digital games: Fallout 4 and The Elder Scrolls V: Skyrim, both developed by Bethesda Game Studios (2015, 2011) and referred to as Fallout and Skyrim for brevity in this study. Both games are designed for entertainment rather than L2 educational purposes. Justification for using these two games in this study is, in part, due to the immense popularity that these games have had around the world. In fact, these games are so popular that Microsoft recently acquired Bethesda Game Studios for $7.5 billion USD (Makuch, 2021). In addition, the games were selected because they were deemed representative of a larger population of games that share similar designs and mechanics. Gamers would likely broadly refer to such designs as open-world or sandbox role-playing games. These terms describe the non-linear nature of the games: tasks or quests do not need to be completed in a particular order, giving a sense of agency to the Player. These are single player games, so there can be only one active player at any given time, which is why the term the Player is used as a proper noun in this study. Open-world games such as Skyrim and Fallout often include mechanics that have the Player following a consistent pattern of gameplay:

1. Create and customize a Player’s Character
2. Complete an introduction or tutorial phase
3. Explore the open virtual environment with liberal options on where to go, what to do, and with whom to interact
4. Interact with non-player’s characters (NPCs) to get quests, information, and equipment
5. Complete quest objectives and gain experience points
6. Level up (strengthen) the Player’s Character to take on more difficult quests
7. Continue to explore and repeat until the game’s eventual conclusion

Additional justification for targeting entertainment games in this study, rather than educational games, comes from a recent DGBLLL meta-analysis (Dixon, Dixon, & Jordan, in review). The researchers found that entertainment games were less common in research designs
compared to L2 educational games; however, entertainment games were found to be generally more effective for L2 learning than those designed for L2 education. Reinhardt (2019) suggests that entertainment games are more effective because they are more engaging and authentic in terms of language use than those designed for L2 education. However, Dixon et al. note that results of the aggregated effects from entertainment games included wide confidence intervals, suggesting the need for more primary research targeting commercial entertainment games in DGBLL contexts.

This target population of games was also deemed linguistically interesting because of the massive amount of contextualized language input that players are exposed to during the 30-100 hours of gameplay typically needed for completion. Illustrating the large amount of language input, Table 2 reports that Fallout has 838,489 words and Skyrim has 493,944 words derived from the three targeted mechanic register categories. Also of note, these games have the option to be played in nine different languages, allowing for a large global consumer base that could target a wide range of L2 learning contexts.

Table 2
Lemma type and token counts for the three registers within the game corpus

<table>
<thead>
<tr>
<th>Mechanic register category</th>
<th>Lemma types</th>
<th>Lemma tokens</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fallout dialogue trees</td>
<td>15,075</td>
<td>811,484</td>
</tr>
<tr>
<td>Fallout quest objectives</td>
<td>1,087</td>
<td>4,894</td>
</tr>
<tr>
<td>Fallout quest stages</td>
<td>1,964</td>
<td>22,111</td>
</tr>
<tr>
<td><strong>Totals</strong></td>
<td><strong>18,126</strong></td>
<td><strong>838,489</strong></td>
</tr>
<tr>
<td>Skyrim dialogue trees</td>
<td>11,584</td>
<td>464,083</td>
</tr>
<tr>
<td>Skyrim quest objectives</td>
<td>1,532</td>
<td>6,452</td>
</tr>
<tr>
<td>Skyrim quest stages</td>
<td>2,342</td>
<td>23,409</td>
</tr>
<tr>
<td><strong>Totals</strong></td>
<td><strong>15,458</strong></td>
<td><strong>493,944</strong></td>
</tr>
</tbody>
</table>

The use of the targeted game mechanics in Fallout and Skyrim
To reiterate, the identified game mechanic register categories (i.e., dialogue trees, quest objectives, and quest stages) are unique in that they serve different purposes in games that employ these designs, justifying their treatment as unique registers in this framework. The first and only spoken game register, dialogue trees, serve the communicative purpose of developing the storylines and narratives within these vast virtual worlds. These language-use instances have the Player and one or more NPC engaging in a branching dynamic conversation which require the Player to make choices that affect the relationships with those NPCs and the broader storylines. In a single game, there are often hundreds of such instances of dialogue trees. An example of a dialogue tree instance from Fallout is seen in Figure 1 in which the Player is given four options in response to an NPC that asked the Player’s Character what they were doing in the Boston area, the setting of Fallout’s post-apocalyptic world. The orange labels in the figure were added for clarity and do not appear in the game.
Depending on which option is chosen, the Player’s Character will say something related to the text displayed for that choice. That is, the “the short answers on the [dialogue trees] sometimes don't sensibly relate to what is actually said” (Adams, 2015, para. 4). Using the dialogue tree instance displayed in Figure 1 as an example, each of the four text choices triggers the Player’s Character to say one of the following lines of dialogue:

1. MINUTEMEN?
   *I was told the Minutemen might be able to help me figure out these schematics.*

2. YOU OWE ME
   *You owe me.*

3. PASSING THROUGH
   *I’m just passing through.*

4. GLAD TO HELP
   *I’ll help if I can.*

In this example, only the second choice is verbatim to the spoken line. For L2 learners, this mismatch could be confusing, and DGBLL practitioners should be aware of such aspects in a game’s design. Despite this mismatch, the context of engaging with NPCs through dialogue trees may offer the type of interaction believed to be important to L2 learning. R. Ellis (2003) suggests L2 learning benefits when interaction occurs in a meaningful and goal-oriented context. The dialogue trees can offer L2 interaction that is meaningful as they give context and narrative to the
goals of the game despite the mismatch between the choices displayed and the actual lines of dialogue that follow a choice.

In Skyrim, dialogue trees are presented in a similar fashion as Fallout, but the Player’s Character does not actually speak any of the selected lines of dialogue, only the NPCs have recorded audio. Another difference is that Skyrim does not limit the number of dialogue options to four as Fallout does. Figure 2 shows an instance of a dialogue tree in Skyrim. The setting of Skyrim takes place in a fictional Tolkien-like fantasy world.

![Figure 2. Dialogue tree instance in Skyrim](image)

Unlike dialogue trees, the quest objectives and quest stages are not as interactive or dynamic. These mechanics do not require a response from the Player. The language from these mechanics are only presented in written form and serve different functions. A function of quest objectives is to direct the Player to the actions needed to complete a quest. The quest stages, on the other hand, give context to the quest objectives through short narratives explaining the background story and justifying those objectives. These mechanics can act as a summary, reminding the Player of what they were doing and why. Figures 3 and 4 illustrate these mechanics in the two games.
Figure 3. Quest objectives and quest stages in Fallout

Figure 4. Quest objectives and quest stages in Skyrim

The *Skyrim* quest stage seen in Figure 3 summarizes past events, telling the Player that they escaped a dragon attack and are free to explore the area. The quest objectives direct the
player to explore areas and interact with NPCs before finding some equipment for their Player’s Character. Typically, quests are scaffolded by building on previous experience and increasing in difficulty as the Player gains new skills and abilities. Purushotma et al. (2008) argue that such scaffolding is similar to well-designed L2 tasks where difficulty increases as language skills improve.

**Research questions**

Using “modification” software and *Python* programs specifically developed for this research, the language files from Fallout and Skyrim were extracted and compiled into a corpus that coded instances of language use into three register categories following the register framework in Biber and Conrad (2019). Each register category was measured on five linguistic variables. These consist of two lexical complexity variables (i.e., richness and sophistication) and three linguistic feature type-token ratios (i.e., the number of pronouns, mental verbs, and activity verbs to the total lemma tokens in each text). Operational definitions of these variables are detailed in the **Method** Section. These variables were selected based on the results of several unpublished pilot studies investigating the linguistic environments of digital games. These variables are then used as predictors in a series of discriminant analyses that determine the extent to which the statistical models can accurately predict the game and the mechanic register category of each of the 6,027 unique texts in the corpus. The aim is to provide empirical insight into gaming environments that can inform future DGBLL research by quantitatively demonstrating the unique linguistic environments that stem from a game’s design and individual game mechanics. Motivated by the call for DGBLL research into game designs and mechanics (see Reinhardt, 2021; Cornillie, 2017), this study aims to answer the following research questions:

1. To what extent can a discriminant analysis model accurately predict both the game and the mechanic from which a text originated based on five linguistic variables?
2. To what extent does the predicting power change when the model only considers the mechanic from which the text originated?
3. To what extent does the predicting power change when the model only considers the game (and not the mechanics) from which the text originated?

**Method**

**Corpus compilation**
The corpus compiled for this study contains the digital language files from Fallout and Skyrim. Compiling the corpus began with extracting the language files from a computer on which the games were installed. The two software suites used to extract the language are publicly available and titled Skyrim Creation Kit and Fallout Creation Kit. Detailing the use of this modification software is outside this study’s scope, but many gaming community websites offer free tutorials for those interested in game modification.
Once all the targeted language files from the games were successfully extracted, they were then categorized and coded according to the game and the mechanic from which the files were derived. Further, each file was related to a single quest which allowed for self-contained naturally occurring units of language, a critical criterion in corpus design (see Egbert & Schnur, 2018). These units are functional in that they serve the communicative purpose of developing a specific storyline or giving the Player direction or background related to a specific objective. Each language file was split into texts containing around 200 words each, allowing the analyses to be based on comparable units of observations despite the variation in the number of texts per mechanic category (see Table 3). Once compiled, the corpus totaled 6,027 texts across the three mechanic categories within the two games and contain a total of 1,332,433 words.

Table 3  
Total texts per game and mechanic register category

<table>
<thead>
<tr>
<th></th>
<th>Fallout</th>
<th>Skyrim</th>
<th>Register text total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dialogue trees</td>
<td>3,700</td>
<td>2,083</td>
<td>5,783</td>
</tr>
<tr>
<td>Quest objectives</td>
<td>24</td>
<td>32</td>
<td>56</td>
</tr>
<tr>
<td>Quest stages</td>
<td>94</td>
<td>94</td>
<td>188</td>
</tr>
<tr>
<td>Game text total</td>
<td>3,818</td>
<td>2,209</td>
<td>6,027</td>
</tr>
</tbody>
</table>

**Linguistic variables**

Five linguistic variables were used to analyze the language derived from the targeted game mechanics. These consist of two lexical complexity measures (i.e., richness and sophistication) and three lexical feature ratio measures (i.e., the number of pronouns, mental verbs, and activity verbs to the total lemma tokens in each text). The three lexical ratio measures were chosen because, if the dialogue in the games is designed to be similar to that of the real world, then the game dialogue should have similar frequencies of linguistic features to that of real world spoken language. Biber (2006) reports that spoken registers rely much more heavily on activity and mental verbs as well as pronouns when compared to written registers (p. 58). Because these features are more common in spoken registers, it was hypothesized that they would be productive in the statistical models’ power to predict the group membership of the texts. That is, their absence or presence could allow the models to discriminate between the spoken and written texts. A complete list of activity and mental verbs can be found in Biber (2006).

Lexical richness is operationalized using mean segmental type-token ratio (MSTTR) which is calculated by dividing the number of unique lemma types by the number of lemma tokens for each text and averaging results for each mechanic category. The second variable, lexical sophistication, is operationalized by quantifying the use of “advanced” words. In corpus analyses, types have been considered advanced if they are found to be less frequent in a target corpus. For example, Bulté and Housen (2014) considered a word advanced if it did not appear in the top 2,000 word frequency band of a comparison corpus. In the current study, a lemma is considered advanced if it is not one of the 1,500 most frequent lemmas in the 2014 spoken
British National Corpus (Love, Dembry, Hardie, Brezina, & McEnery, 2017). In addition to this criterion, the lemma could not be a pronoun or be in the lists of mental or activity verbs, allowing the use of less common words to be operationalized and quantified.

**Discriminant analyses**

After each of the texts from the corpus was measured on the targeted linguistic variables, the variables were then used as predictors in three discriminant analyses. Discriminant analysis (see Norris, 2015) is used to predict the group membership of a set of observations based on predictor variables that form *functions*. These functions measure the extent to which the combinations of variables can accurately predict texts as belonging to the correct mechanic and game category based on their linguistic environments. The first discriminant analysis coded the segments of text for both the game and the mechanic from which the texts originated. The second coded only for mechanic, and the third coded only for game. The accuracy of each of the three discriminant analyses was then compared to determine which model (game and mechanic, only game, or only mechanic) had the strongest power to discriminate the group membership of each of the 6,027 texts.

Several tests were conducted to check the statistical assumptions recommended for discriminant analyses (see Poulsen & French, 2020). A Shapiro-Wilk normality test indicated some issues with normality; however, the histograms and QQ plots showed a high degree of normality for most variable-category comparisons. Pairwise comparisons showed no evidence of curvilinearity. Less than 2 percent of the total data contained outliers, so they were not removed. All bivariate correlations between predictor variables were less than +/- .90. Variance inflation factor (VIF) values were mostly below the recommended 2.5 value. Based on these results, the decision was made to continue with the discriminant analyses.

**Results**

Means and standard deviations of each of the five variables were calculated for each mechanic register category in both games. Tables 4 and 5 reveal some notable patterns, showing that dialogue trees in both games had higher mean ratios of sophistication, richness, and pronouns compared to the other mechanics. Mental verbs and activity verbs tended to show very little difference across the categories with the dialogue trees showing slightly higher ratios.

**Table 4**

<table>
<thead>
<tr>
<th></th>
<th>Fallout dialogue n = 3,700</th>
<th>Fallout quest objectives n = 24</th>
<th>Fallout quest stages n = 94</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>Sophistication</td>
<td>.28</td>
<td>.04</td>
<td>.15</td>
</tr>
<tr>
<td>Richness</td>
<td>.55</td>
<td>.06</td>
<td>.51</td>
</tr>
<tr>
<td>Pronouns</td>
<td>.15</td>
<td>.04</td>
<td>.01</td>
</tr>
<tr>
<td>Mental verbs</td>
<td>.04</td>
<td>.02</td>
<td>.02</td>
</tr>
</tbody>
</table>
Table 5

Skyrim mechanics mean and standard deviation on linguistic measures

<table>
<thead>
<tr>
<th></th>
<th>Skyrim dialogue $n = 2,083$</th>
<th>Skyrim quest objectives $n = 32$</th>
<th>Skyrim quest stages $n = 94$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
</tr>
<tr>
<td>Sophistication</td>
<td>.28</td>
<td>.04</td>
<td>.17</td>
</tr>
<tr>
<td>Richness</td>
<td>.56</td>
<td>.06</td>
<td>.51</td>
</tr>
<tr>
<td>Pronouns</td>
<td>.15</td>
<td>.03</td>
<td>.01</td>
</tr>
<tr>
<td>Mental verbs</td>
<td>.04</td>
<td>.02</td>
<td>.02</td>
</tr>
<tr>
<td>Activity verbs</td>
<td>.03</td>
<td>.02</td>
<td>.04</td>
</tr>
</tbody>
</table>

A canonical discriminant analysis revealed that five functions account for the variance in linguistic variables across text categories. The first function had the strongest discriminating power accounting for 79 percent of the variance, followed by the second function accounting for 13 percent, and the final three accounting for less 8 percent of the variance in the targeted linguistic variables. Only Functions 1 and 2 were included in the models because together these two functions account for almost 93 percent of the variance.

Figure 5 visualizes where each of the texts fell as measured by Function 1 (x axis) and Function 2 (y axis). These functions are combinations of the five linguistic variable measures. Each dot represents one of the texts in the corpus. The large dots represent the mean position of each of the mechanic register categories as measured by the two functions. Figure 5 illustrates that the texts in same mechanic register category in both games are in close proximity to one another and have much overlap. For example, the dialogue trees in both games, which had the highest number of texts, are very close to one another, represented by the large red dot and the large teal dot. The quest objective and quest stage means are also near one another at about 2.5, -1 and 1.5 respectively. This close proximity gives evidence that similar linguistic environments exist within the same mechanics across the two games when measured on these five linguistic variables. Thus, generalizations regarding the linguistic environment of a game as a whole could be problematic as specific mechanics appear to have very unique linguistic environments, but the linguistic environments of the mechanics remain quite similar despite the fact that they were derived from two different games with very different fictional settings.
To further test for evidence of similar linguistic environments (i.e., registers) across games, the discriminating power of the model was analyzed. In answering Research Question 1 regarding the discriminating power of a model that considers both the games and the three mechanic registers, the confusion matrix in Table 6 reports the extent to which the model could accurately predict the texts as belonging to one of the six mechanic register categories. Two statistics quantify the accuracy of the model’s predicting power, which are precision and recall rates (see Biber & Egbert, 2015). The rows indicate the precision rate, which is the number of correct text predictions divided by the total number of predictions for a category. The columns indicate the recall rate, which is the number of texts that actually belong to a mechanic category divided by the number of correct predictions. The percentages represent the accuracy of the model (i.e. precision and recall).

For the Fallout dialogue trees, the model correctly predicted 3,624 texts. However, looking at the row total, it predicted a total of 5,788 texts as belonging to Fallout dialogue trees, meaning that the precision rate for Fallout dialogue trees is only 63 percent (3,624/5,788). The recall rate, indicated in the column total, is 98 percent which means that out of the 3,700 Fallout dialogue tree texts, 3,624 were correctly predicted. It is interesting that although the precision rate for Fallout dialogue is only 63 percent, 2,046 of the texts were incorrectly predicted to be in the so-called “sister” category of Skyrim dialogue trees. This suggests that much of the
inaccuracy was due to the similarities in linguistic environments within the same mechanic across the two games. This pattern is mostly consistent within the other mechanic registers. Seven of the texts in Fallout quest objectives were incorrectly predicted to be in Skyrim quest objectives. The only register that this pattern appears to slightly deviate is with quest stages. Many of the Fallout quest stages texts were incorrectly predicted to be in the Fallout dialogue tree register category. In short, the majority of inaccuracies were often across games but not mechanics, providing further support for the argument that a single game can have multiple linguistic environments that are consistent across different games.

Table 6
Confusion matrix

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fallout Dialogue</td>
<td>3,624</td>
<td>0</td>
<td>61</td>
<td>2,046</td>
<td>1</td>
<td>56</td>
<td>5,788</td>
<td>63%</td>
</tr>
<tr>
<td>Fallout Q. Obj.</td>
<td>1</td>
<td>9</td>
<td>0</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>17</td>
<td>53%</td>
</tr>
<tr>
<td>Fallout Q. Stage</td>
<td>23</td>
<td>0</td>
<td>7</td>
<td>6</td>
<td>0</td>
<td>6</td>
<td>42</td>
<td>17%</td>
</tr>
<tr>
<td>Skyrim Dialogue</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>5%</td>
</tr>
<tr>
<td>Skyrim Q. Obj.</td>
<td>3</td>
<td>15</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>44</td>
<td>55%</td>
</tr>
<tr>
<td>Skyrim Q. Stage</td>
<td>48</td>
<td>0</td>
<td>26</td>
<td>28</td>
<td>0</td>
<td>32</td>
<td>134</td>
<td>24%</td>
</tr>
<tr>
<td>Total</td>
<td>3,700</td>
<td>24</td>
<td>94</td>
<td>2,083</td>
<td>32</td>
<td>94</td>
<td>6,027</td>
<td></td>
</tr>
<tr>
<td>Recall</td>
<td>98%</td>
<td>38%</td>
<td>07%</td>
<td>&lt;01%</td>
<td>75%</td>
<td>34%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

To measure the extent to which the predicting power of the model changed when the game grouping variable was removed (Research Question 2), the texts were coded into three categories instead of six, categories including only the three mechanic register categories, excluding the game grouping variable. The confusion matrix (Table 7) reports that this second discriminant analysis saw substantially improved precision and recall rates. The model could correctly predict the group membership of at least 90 percent of the texts in dialogue trees and quest objectives. However, quest stages, while much more accurate than the previous model, could only accurately predict about 40 percent of the texts as many quest objective texts were incorrectly predicted to be in the dialogue category. The group mean plot in Figure 6 illustrates a degree of overlap between the dialogue tree texts and the quest objective texts, suggesting that these two mechanics share some moderate linguistic similarity. However, the distance between group means (the large red and blue dots) indicate that these two mechanics still maintain largely unique linguistic environments.

Table 7
Confusion matrix with collapsed categories

<table>
<thead>
<tr>
<th></th>
<th>Dialogue</th>
<th>Q. Obj.</th>
<th>Q. Stage</th>
<th>Total</th>
<th>Prec.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dialogue trees</td>
<td>5,664</td>
<td>1</td>
<td>114</td>
<td>5,779</td>
<td>98%</td>
</tr>
<tr>
<td>Quest objectives</td>
<td>6</td>
<td>55</td>
<td>0</td>
<td>61</td>
<td>90%</td>
</tr>
<tr>
<td>Quest stages</td>
<td>113</td>
<td>0</td>
<td>74</td>
<td>187</td>
<td>40%</td>
</tr>
</tbody>
</table>
Total | 5,783 | 56 | 188 | 6,027
Recall | 98% | 98% | 39% | 

**Figure 6.** Group means as measured by Function 1 and Function 2 with only mechanic categories

Finally, to answer Research Question 3, a third discriminant analysis was conducted by coding the texts using only the game from which the texts were derived. One category contained all the texts from Fallout, and the other contained those from Skyrim. Table 8 shows that the model cannot predict which texts belong to which game as all texts were inaccurately predicted to belong to Fallout (as seen by the first row in Table 8). This gives evidence that, when comparing the linguistic environments of the games without consideration of the game mechanics, the model has no discriminating power to distinguish any differences between any of the 6,027 texts.

**Table 8**

*Confusion matrix with only game title categories*

<table>
<thead>
<tr>
<th></th>
<th>Fallout</th>
<th>Skyrim</th>
<th>Total</th>
<th>Prec.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fallout</td>
<td>3,818</td>
<td>2,209</td>
<td>6,027</td>
<td>63%</td>
</tr>
<tr>
<td>Skyrim</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>NA</td>
</tr>
</tbody>
</table>
Discussion and direction for future research

The results of this study give strong evidence regarding the problematic nature of taking a “game-as-a-whole” or genre approach to DGBLL research. Taken as a whole, games may appear to be quite linguistically similar or even indistinguishable as evidenced by the results. In contrast, when considering the specific mechanics from which instances of language were derived, unique linguistic environments or registers become clearly distinguishable. Further, the use of language in each mechanic category has a high degree of consistency across the games. Thus, these findings suggest that DGBLL researchers could better generalize results through research designs that target specific game designs or mechanics rather than broadly generalizing about a particular genre or specific game title. This finding gives empirical support to Reinhardt’s (2021) claim that “generalizing the implications from the study of L2 gameplay with one title to other titles, even if they are in the same genre, may be risky. A better approach is to focus on the features of the game that are more universal, that is, the mechanics themselves” (p. 2). This is because genre definitions and descriptions can vary greatly depending on the source describing any one specific game as a widely-accepted and meaningful categorization of genres has yet to be established. Thus, researchers could use game mechanics, which are more universal, when generalizing the results of DGBLL research.

To illustrate some of the linguistic differences in these game mechanics, a typical quest objective instance is transcribed below in Excerpt 1. The associated quest stage is seen in Excerpt 2, and a dialogue tree text is seen in Excerpt 3. In Excerpt 1, it is clear that the language used is less complex than that of the quest stage text in Excerpt 2. One explanation is that these texts function to give clear unambiguous directions to the Player. This difference helps explain the lower ratio of advanced words within quest objectives which was .15 compared to quest stages’ mean ratio of .21 (see Results). Also of note, the quest objective excerpt does not contain a single pronoun, which made the pronoun ratio variable a robust predictor of group membership. The mean ratio of pronouns to total lemmas was only .01 for quest objectives. In contrast, the quest stage mean pronoun ratio was .11. This higher use of pronouns is likely due to the quest stages’ function, acting as a journal written in first-person recording recent events in the game and giving context to objectives. Pronouns in dialogue trees (see Excerpt 3) generally had the highest pronoun ratio which was .15. This higher use of pronouns aligns with corpus findings that report pronouns are quite frequent in real-world spoken conversation due to the shared context and background knowledge of the interlocutors (Biber et al., 1999).

Excerpt 1. From quest objective file InstM01.txt

Talk to Isaac Karlin
Deliver the Seeds to Roger Warwick
Follow Roger Warwick

<table>
<thead>
<tr>
<th>Total</th>
<th>3,818</th>
<th>2,209</th>
<th>6,027</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recall</td>
<td>100%</td>
<td>0%</td>
<td></td>
</tr>
</tbody>
</table>
Talk to Roger Warwick
Discover Bill's Plans
Talk to Cedric Hopton

Excerpt 2. From quest stage file InstM01.txt
I failed in my mission to covertly deliver genetically-modified seeds to Warwick Homestead. I need to report this to Dr. Karlin at the Institute.
Doctor Holdren of the BioScience division asked me to speak to Dr. Isaac Karlin, who needs my help with a mission on the surface.

Excerpt 3. From dialogue tree file InstM01Post.txt
We're already seeing remarkable results from the new specimen at Warwick.
The early results from those new seeds you delivered are remarkable.
One of the gourds is growing in really huge!
You should take a look at the gourd patch. We've got a prize-winner for sure.

To reiterate, this study did not measure the effectiveness of these various mechanics for L2 learning as this type of analysis was outside the scope of the current study. At the same time, inferences can be drawn based on relevant SLA theory, offering exciting opportunities for future DGBLL research. For example, the dialogue trees may offer L2 interaction that is meaningful by offering context and narrative to the goals of the game, providing an engaging experience for L2 gamers. Furthermore, the games’ dialogue appears to resemble real-world conversations which would allow for L2 knowledge gained from the games to be applied to real-world contexts. However, more research is needed to investigate the extent to which the game dialogues resemble real-world conversation. In particular, dialogue trees could be especially beneficial when playing a game with which an L2 gamer is already familiar. To this point, Reinhardt (2019) suggests that replaying a game in an L2 may allow one to focus on the language rather than the rules of the game (p. 117). This familiarity can allow language input to be processed more easily. Shin, Dronjić, and Park (2019) have shown that working memory is likely less taxed when a learner has preexisting background knowledge, allowing for greater comprehension of L2 input. Quest stages and objectives generally repeated words more often than dialogue trees. L2 gamers might benefit from these repeated exposures from a usage-based perspective of L2 acquisition. N. Ellis (2019) explains that this processing of frequent input can allow for incidental form and meaning connections to be made through associative learning, leading to habitual and automatic access of those forms. That is, the form requires less conscious effort to understand or produce as more examples from a meaningful context are processed.

Due to the limitations of this study consisting of only three mechanic registers and two games, the results can only be cautiously generalized to other games in the target population.
Further, the two games were developed by the same studio, Bethesda. Thus, additional research is needed to confirm these initial findings from a variety of games and game studios. A larger-scale study could incorporate language from additional games and mechanics to further analyze the environments within mechanics and across several games from this targeted population (i.e. open-world games). Nevertheless, the results do give strong initial support that language derived from specific mechanics have distinct linguistic environments and that these environments appear to be largely consistent across different games when comparing the same mechanic register category.

One challenge for DGBLL researchers is the lack of a reliable list of game mechanics as developers are often imagining new mechanics and augmenting old ones as a means to create their next commercial success. Addressing this challenge, Reinhardt (2019) has published an extensive list of game mechanics coupled with pedagogical principles to help guide research in DGBLL contexts. For example, one of many avenues of research that Reinhardt discusses is the affordance of contextualized language learning through a narrative mechanic, such as dialogue trees, which could lead to semantically-related vocabulary learning. In another resource, Adams and Dormans (2012) discuss in depth the complex systems that make up mechanics and, although not written from an SLA perspective, it could lend great insight for understanding the design of digital game mechanics. The results of this study suggest that DGBLL researchers can add precision to research findings using designs that consider mechanics rather than generalizing about a particular game or genre. Adding this degree of precision to future research can better inform application to DGBLL contexts and inform the development of effective digital tools designed for L2 education.
References


