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CONSISTENT GAMING SKILL DEMOGRAPHICS IN ACADEMIC RESEARCH

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ABSTRACT

Video games are a popular topic in academia, encompassing many research subtopics. Often researchers investigating video game subjects partition the participants bythe participant's familiarity with video games. Unlike other demographic categories on which research subjects are divided, such as age range or income, sorting participants intogamer skill categories, such as "Expert Gamer", has no objective consensus on what the labels should be. The inconsistency in terminology makes comparison between research works impossible. Hours per week is often a standard but does not provide statistical significance with many factors and is not as objective as it may seem. This paper highlights this problem, collects demographic questions in existing research, and showcases the data collected from a user study with these questions. The results show that self-chosen categories are a statistically significant metric and is recommended as an easy-to-obtain value.

KEYWORDS

Gamer Skills, Gamer Demographics, Video Games, HCI

1. INTRODUCTION

Academic research containing human subjects requires a standardized method of categorizing study participants into demographic labels for accurate analysis of results. Standard demographics include age, gender, ethnicity, or income. One such way to categorize participants when involved in video game research is the participant's perceived gamer experience level. Categorizing participants into "Expert" or "Novice" groupings could control for the differences that arise from players' varying levels of expertise, experience, and familiarity with a gaming system. The problem arises when trying to find a consensus on how to categorize an individual's a specific gaming skill.

One option from Adams and Ip (2002) is a 15-factor gamer classification method based on the previous work of Adams (2000) and Kim (2001). Each factor is given a different weight based on importance, and each player is given a player dedication score. These scores are then used to categorize gamers into “ultra casual”, “casual”, “transitional/modern”, “hardcore”, and “ultra hardcore”. This classification method could be used as a standard and is a great starting point for defining important questions and factors, but a standardized weighting should be created that all researchers use. Adams and Ip (2002) state: “Moreover, in applying the classification procedure, weightings can be determined arbitrarily according to the importance the marketer perceives them to hold for his own purposes”. Further, the authors go on to suggest ways to quantify each of the 15 factors in a vague way, but they did not provide a specific standardized set of questions. The lack of a standardization results in a body of research that cannot be compared with any accuracy, making it difficult to draw conclusions based on data from multiple studies.

A different option used by researchers is hours per week (HPW) spent playing video games. Participants can be split into groups based on the numerical hours of exposure they have with the subject and is acceptable to use in that context. The use of HPW to define what is or isn’t an “Expert Gamer”, however, is misguided. Expertise in a field is not directly a result of sheer quantity of hours but the quality of the hours spent (Ericsson et al., 1993; Ericsson et al., 2016). The tendency towards the use of hours per week may be a result from the desire to have an objective, quantitative measurement for the demographic division. However, hours per week is not a truly objective measurement, but instead a subjective one. It requires participants to estimate based on their own mental ability what they did in the past, which is a subjective opinion. Additionally, a primary effect of one of the most popular enjoyment definitions for game enjoyment, Game Flow, is a warped sense of time (Sweetser and Wyeth, 2005). If a gamer enjoys playing video games, their estimation of the hours spent per week on video games is unavoidably subjective.

For our research, we gathered information from multiple academic sources that divided participants into gaming skill demographics to examine the metrics used. We then provide analysis of correlations in these metrics. The papers were selected because they detailed the specific metric used so that the metric could be recreated in our own study, as described in Section 3. Finally, we provide analysis of correlations in these metrics. The research questions for this work were:

- **R1**: Is there a consensus for the metric of hours per week used to define gaming skill categories?
- **R2**: With what factors does hours per week correlate?
- **R3**: With what factors do other metrics, used by previous research, correlate?
- **R4**: What is the most reliable metric for dividing participants into gaming skill categories?

2. SURVEY OF RELATED WORKS

For this study we surveyed multiple peer-reviewed academic publications for the purpose of identifying a clear metric for video game player categorization. Unlike other demographic categories on which research subjects are divided, such as age range or income, sorting participants into gamer skill categories has no objective consensus on what should be used for the gaming skill labels. The metrics used to determine these non-standardized labels vary greatly, even within papers that agree on a demographic labeling scheme. We selected papers that mentioned categorization and provided the specific questionnaire metrics used to create the categorization. The following subsections describe our findings concerning gamer skill demographic categories and the metrics used for partitioning.

2.1 Demographic Category Labels

The terminology used across papers is inconsistent when it comes to how gaming skill should be labeled. Some researchers label the more experienced gamers as "hardcore" (Baumann et al., 2018; Paaßen et al., 2017; Poels et al., 2012) while others use the terminology "expert" (Boot et al., 2008; Liu et al., 2020; Marre et al., 2021; Shafer et al., 2011). The use of the "expert" label has vastly different qualification definitions between research works. Two different groups of researchers use the label "expert" gamers but the research works do not use the same metric to make the distinction between participants with the "expert" label versus those who do not have the "expert" label. An alternative label distinction is a simple distinction between "video game player" (VGP) and "non-video game player" (NGVP) (Castel et al., 2005; Feng et al., 2007; Green and Bavelier, 2006). This casts a large net for the VGP category, under which even casual players can fall, and makes no distinction between VPGs who play the minimum required by the metric versus those who play far beyond the minimum.

Paaßen et al. (2017) reviewed the existing literature on gender and gaming to investigate the accuracy and effects of the gamer stereotype. They proceed to evaluate the meanings of "casual" and "hardcore gamers", looking at criteria such as time investment, gaming knowledge, playing attitudes, buying habits, game genre, and self-identification to define those terms. None of those criteria except for self-identification could be used reliably to define "hardcore" gamers. Even video game skill was not mentioned as an identifying feature. They conclude that based on their review of relevant literature the definition of "gamer" is inconsistent and not standardized.

To maintain consistency for this work, the terminology used will use "expert" instead of "hardcore" as a label for a participant experienced with video games. Research which uses a different terminology than "expert" will be noted with parentheses.

2.2 Time Spent Per Week

A common metric found for determination of which demographic label a participant fell under is the number of hours per week the participant spends playing video games. The assumption among researchers that the skill of a gamer has statistical significance with the time spent playing video games is not an outlandish one but is untested and not standardized. Further, researchers that use play time as a gaming skill demographics have a wide range of metric cut-offs, from 20 hours per week for an expert gamer (Baumann et al., 2018), to at least one hour per day (Poels et al., 2012), to playing games on at least four days a week (Green et al., 2003). Table 1 shows a summary of the hours per week cutoff for category of gaming skills, where the labels used for these groups varied by research. There is a large discrepancy in defining what an expert gamer is among these papers, with some setting a much higher bar to cross than others.

Baumann et al. (2018) use one of the highest cutoffs, 20 hours per week, but cite Poels et al. (2012) for their reasoning; Poels et al. used at least one hour per day. The 20 hours per week Baumann et al. used from comes from the average time spent of those labeled as “expert” (“hardcore”) gamers as discovered by Poels et al. By using 20 hours per week as the cutoff, the work by Baumann et al. can’t compare their data for “expert” (“hardcore”) gamers with Poels et al., despite citing research by Poels et al.

Table 1. A summary based on the papers that used some form of hours per week as a categorization for gamers

Research Author(s)	Hours Per Week Range	Label
Marre et al. (2021)	> 4	Expert
Feng et al. (2007)	> 4	Players
Castel et al. (2005)	> 4	VGP
Boot et al. (2008)	> 7	Expert
Poels et al. (2012)	> 7	Hardcore
Baumann et al. (2018)	> 20	Hardcore
Pontes et al. (2015)	> 30	Disordered

Other papers that used hours per week as a metric to categorize gamers only defined participants as video game players (VPGs) or non-video game players (NVPGs) (Castel et al., 2005; Feng et al., 2007; Green and Bavelier, 2006). Castel et al. (2005) define VGPs as people who had played action video games at least four times a week for a minimum of 1 hour per day and for the previous six months while NVGPs had less than 1 hour per month of video game playing experience. Green and Bavelier (2006) had a criteria at a vague threshold, with VGPs having 3-4 days a week of action video game usage for the previous six months. Marre et al. use at least 4 hours per week to determine an “expert” gamer, but this same amount of HPW is used to determine the less specific label of “Players” and “Video Game Players” by Castel et al. (2005) and Feng et al. (2007) respectively.

2.3 Self-Reporting Skill

Another metric to obtain gamer categorization is a self-reported gamer label. Motivation for the use of a self-reported skill category is that a self-applied metric captures the participants self-perceived skill set. How a participant sees themselves is a quantifiable, yet subjective, metric. But if the wording of the question used by different researchers remains the same, a self-applied metric could be compared between research projects.

Eight works we reviewed used questionnaires containing either likert-scale questions or multiple-choice questions where participants reported their perceived skill level (Bracken and Skalski, 2006; Chesney et al., 2014; Liu et al., 2020; Matthews and Gilbert, 2020; Matthews, 2015; Schrader and McCreery, 2008; Shafer et al., 2011). As with labels based on time spent playing video games, the scales used for self-reported gamer label were not consistent. Participants in data reported by Liu et al. (2020) were asked to “rate yourself as a computer gamer” on a 5-point scale while Shafer et al. (2011) measured skill level with the question “How would you rate your skill at the game”, with responses ranging from “expert” to “none”. Table 2 shows the summary of questions used in the related works to obtain a self-reported skill category.

There is evidence that a self-reported skill level does match with in-game metrics. Huang et al. (2013) and Liu et al. (2020) found that self-rated skill was a strong predictor of player performance on average. However, as Table 2 catalogs, the types of questions used across research are inconsistent and the labels chosen by researchers vary greatly. For example, the label for “non-gamer” had several options: Bracken et al. (2006) used “noobie”, Matthews and Gilbert (2020) used “Newbie/Non-Gamer”, and Schafer et al. (2011) used “None”.

Table 2. A summary of the questions used by researchers for a self-reported skill metric

Author(s)	Question Used	Response Range
Bracken et al. (2006)	“I am a good video game player.”	1 : “strongly agree” … 5 : “strongly disagree”
Schrader and McCreery (2008)	Asked participants to select their gaming level	1 : noobie 2 : novice 3 : proficient 4 : expert 5 : master
Matthews (2015)	Asked participants to assess their skill level	1 : “well above average” … 5 : “well below average”
Matthews (2013)	Asked participants to assess their skill level	1 : “expert” … 5 : “poor”
Matthews and Gilbert (2020)	“Which of the following describes your experiences with video games?”	Newbie/Non-Gamer Casual Gamer Frequent Gamer Expert Gamer
Chesney et al. (2014)	“Do you play video games?” “Do you consider yourself a gamer (someone who plays video games frequently)?”	Yes/No Demographic categories: -[N/*] non-gamer -[Y/N] gamer -[Y/Y] frequent gamer
Shafer et al. (2011)	“How would you rate your skill at the game?”	“Expert” … “None”
Shafer et al. (2011)	“Rate how often you play computer games”	“Every Day” … “Never”

3. METHODOLOGY

Our survey was designed with the intention to collect a large amount of data using several demographic metrics. The questions created were either directly lifted from previous research or based on data collected by previous research. Additionally, each of the 15-factors proposed by Adams and Ip (2002) were converted into Likert statements. For example, factor 1, “Play games over many long sessions”, was changed to “I play video games over many long sessions”. Any other metrics discovered in the related works were also converted to Likert statements and included in the survey. The survey also included a few non-Likert scale questions. A free-form question requested how many years have the participant has played video games. A multiple-choice question allowed participants to select a self-assigned label out of five categories: Expert Gamer, Intermediate Gamer, Casual Gamer, Novice Gamer, or Non-Gamer. In conjunction with the self-assigned label question, a follow up free-form question asked what factors they considered for choosing the label in the previous question.

The survey was separated into four sections. The first section contained an identification section and obtained participant's consent. Section two consisted of 25 questions that were measured on a 5-point Likert scale. The third section asked about the participants' typical gaming behaviour and preferences such as their preferred genre and the number of hours spent playing video games. The last page obtained demographic information. All questions on the form were optional except for the informed consent and payment information.

The survey was posted on Prolific and among gaming communities on Discord, a messaging application. A total of 116 responses were received. Each participant was paid $5.00 upon completion of the survey. Of these participants, 67% (77) were male, 29.6% (34) were female, and 3.5% (4) were non-binary. The average age of the participants was 26, with the age range being 18 to 42.

4. ANALYSIS

Statistical analyses were performed using the R programming language. We selected a p-value significance threshold of 0.05, using contingency tables for visualization of patterns in the data. Contingency tables use proportional rectangles to represent numerical summations within a group. The wider a column the more participants fell into those subdivision of categories. The taller a block within a column the more participants who answered with that value. Because the height of the rows can change, the order in which the blocks show indicate which answer value it represents. These blocks are also color-coded to assist in readability. The chi-squared p-value was reported beneath the title of each table and will appear as "p<0.001" if the p-value falls below the threshold value. The wilcoxon pairwise analysis results were represented by alphabetical labels along the bottom of the table. If two columns shared a letter, they were not significantly different; columns with different letters were statistically different.

4.1 Likert Scale Comparisons

The independent variables used for our Likert scale analyses were hours played per week and self-chosen gamer experience level ("Gamer Category" in the tables). Participants were given five options for the Gamer Category responses but only two participants labeled themselves as a "Novice Gamer" and none chose the "Non-Gamer" label. When analyzing Gamer Category as an independent or dependent variable, those labeled "Novice Gamer" were combined with "Casual" due to the relatively small number of responses.

No standard grouping for hours per week is apparent, therefore two approaches were used. The first categorization for hours per week responses was to group into five categories based on recommendation by Pontes et al., 2015. The five categories were <7, 8-14, 15-20, 21-30, and >30. Pontes et al. does recommend the two separate categories of 31-40 and >40, however few of our participants answered >40, and therefore the two categories were combined. The second categorization aimed to provide the same statistical power to hours per week as self-chosen gaming labels. The more subdivision of participant data into categories, the weaker the statistical power. The gaming labels were grouped into three categories, therefore the hours per week were broken into the 33% and 67% percentiles (12 and 25 respectively) to provide an almost equivalent statistical power.

The dependent variable was the value response to the Likert questions from the questionnaire. The values range from 1 as "strongly disagree" to 5 as "strongly agree", with 1 at the top of the contingency table and 5 at the bottom, with the colors purple and yellow respectively. The Likert statement analyzed is the top title in the figures.

Figure 1 shows the contingency tables for the responses to the statement "I am a good video game player" (Bracken et al., 2006). The hours per week categories were not statistically significantly different from each other (Figures 1a and 1b) for either approach to subdivision of hours per week range. All the self-chosen gaming labels were statistically significantly different (Figure 1c). "Casual/Novice" disagreed with the statement the most, "Intermediate" was either neutral or agreed with the statement, while "Expert" had the strongest agreement in responses. This analysis showed that it was not the number of hours put into a subject that builds a participant's confidence in their skill. One could spend several hours each day practicing something and still not consider themselves an expert in that subject. The answers in the follow-up free-form question querying participants about which factors influenced their decision of selecting a self-chosen gamer experience label support this figure. Out of the responses, the one of the most mentioned codes was "skill". This code was defined as gaming ability, how well the player can complete in-game tasks, and how "good" they are compared to other players. Skill was mentioned by 33% of all respondents. Breaking into self-chosen gaming labels, the skill code was noted in 26% of casual players, 36% of intermediate players, and 35% of expert players.

Figure 2 shows the contingency tables for the responses to the question "I know a lot about video games". The hours spent playing video games each week was not a significantly related to the respondents' statements about video game knowledge (Figure 2a) for the five ranges subdivision. The chi-squared value for three ranges for hours per week was not significant, despite pairwise analysis finding a difference between the <12 and 12-24 groups (Figure 2b). All three categories of self-chosen gamer label were (Figure 2c). The participants who identified as "Casual/Novice" were the only ones to answer "strongly disagree" to this statement. "Expert" participants selected neutral or agreement options and did not select "disagree" or "strongly disagree".

One of the factors from Adams and Ip (2002) is "Has a comparative knowledge of the video game industry". Figure 3 shows the responses to the Likert equivalent statement. The chi-squared values for both hours per week categorization approaches is not statistically significant, see Figure 3a and 3b. The self-chosen gaming labels has a low chi-squared p-value and statistically significantly different pairwise comparison for all three categories of "Casual/Novice", "Intermediate", and "Expert", see Figure 3c.

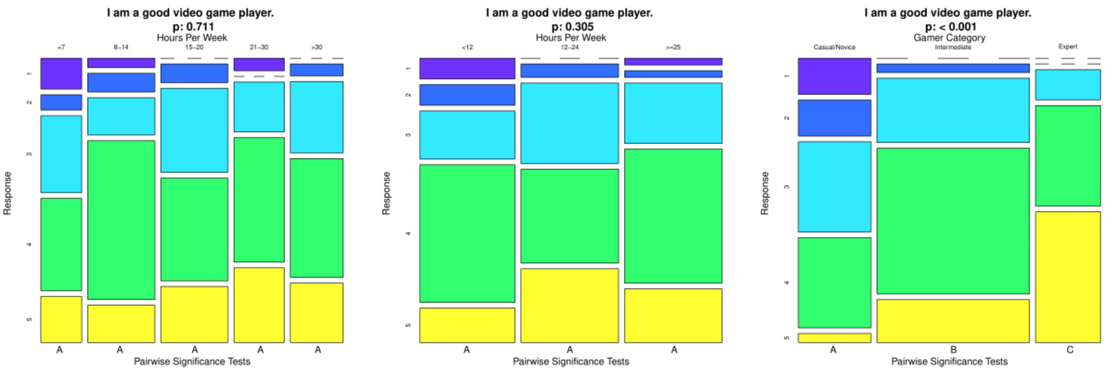
Hours per week did have significance with the Likert responses to the statement "A lot of my free time is spent playing video games", unsurprisingly. Figure 4 shows the contingency tables for the responses to this statement. The five-category breakdown in Figure 4a showed statistically significant differences between <7 and >30 categories, and Figure 4b shows that all three percentile categories were statistically significantly different. Despite this, the self-chosen gaming label (Figure 4c) performs better than the five category hours per week, and nearly as well as the percentile categories of hours per week, with a small difference in chi-squared values ($p=0.0011$ for percentile hours per week and $p=0.0053$ for self-chosen gaming label).

The statement “I play video games over many long sessions” also showed statistical significance for both hours per week breakdowns (Figures 5a and 5b) with more hours per week corresponding with a stronger agreement to the statement. However, the pairwise analysis was not statistically significant for all columns. The self-chosen gaming labels (Figure 5c) had pairwise statistical significance for all three label categories, with “Expert” gamers answering “strongly agree” more often than either “Intermediate” or “Casual/Novice”.

Contingency tables were created for the 13 of the 15 factors that were converted to Likert response statements for this study. Table 3 shows which tables had statistical significance for hours per week and self-chosen gaming labels. The table lists the suggested weighting by Adams and Ip for each of those factors and two significance columns. An asterisk in the Sig. HPW5, Sig. HPW3, or Sig. Labels columns indicates that we found statistically significant differences, as demonstrated in Figures 1 through 5, based on either the hours per week 5-column, hours per week 3-column, or self-choosing gaming labels. In our study, only one of the 15 factors (“Play games over many long sessions”) was significantly associated with either breakdown of hours per week (Figure 5). The factors “Play games over many long sessions”, “Comparative knowledge of the industry”, “Technologically savvy”, “Have the latest high-end computers/consoles”, and “Hunger for gaming-related information” were significantly associated with the self-chosen gaming labels. No statistical significance was found for the highly rated factors of “Discuss games with friends/bulletin boards”, “Much more tolerant of frustration”, and “Desire to modify or extend games in a creative way”, with the suggested weights of 10, 9, and 8 respectively.

4.2 Code Book

The free form question asking, “What factors did you consider for choosing the label in the above question?”, in reference to self-chosen gaming experience labels, was converted into a code book. Twenty-four codes were created for the study. Frequencies of each code were recorded for all participants and broken into the self-defined gamer labels of Casual, Intermediate, and Expert. Novice was omitted due to the low number of participants. Table 4 shows the five most frequent codes.

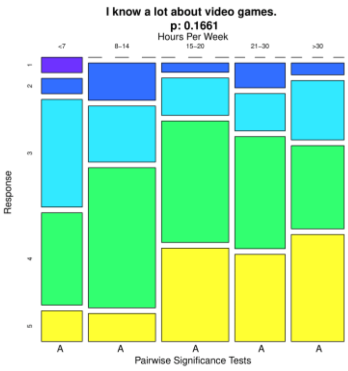


(a) Compared to hours per week

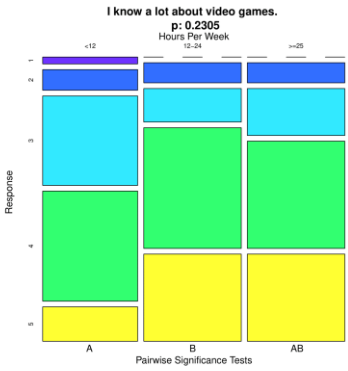
(b) Compared to percentile hours per week

(c) Compared to self-chosen gaming label

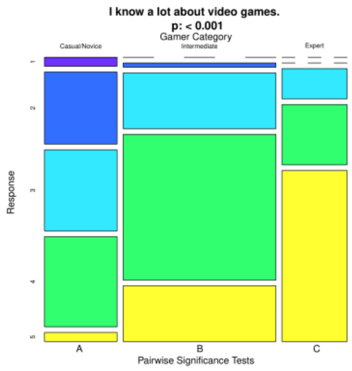
Figure 1. Responses 1 (Strongly Disagree) to 5 (Strongly Agree) to the statement “I am a good video game player”



(a) Compared to hours per week

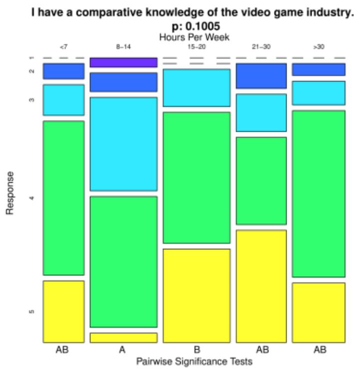


(b) Compared to percentile hours per week

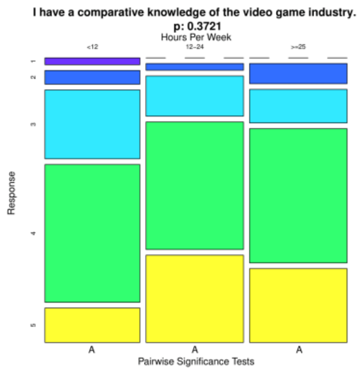


(c) Compared to self-chosen gaming label

Figure 2. Responses 1 (Strongly Disagree) to 5 (Strongly Agree) to the statement “I know a lot about video games”



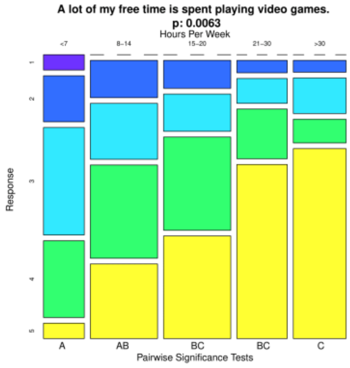
(a) Compared to hours per week



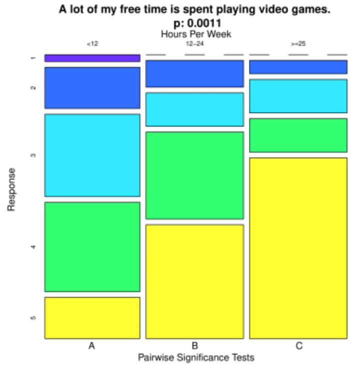
(b) Compared to percentile hours per week

(c) Compared to self-chosen gaming label

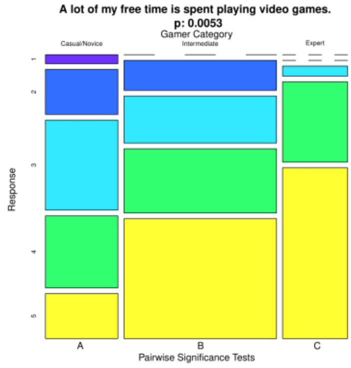
Figure 3. Responses 1 (Strongly Disagree) to 5 (Strongly Agree) to the statement “I play video games over many long sessions”



(a) Compared to hours per week



(b) Compared to percentile hours per week

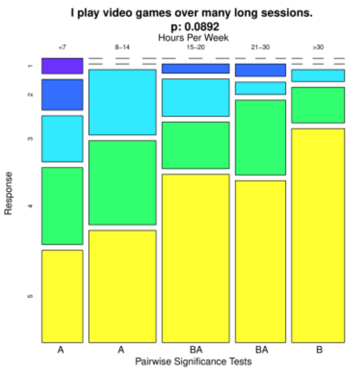


(c) Compared to self-chosen gaming label

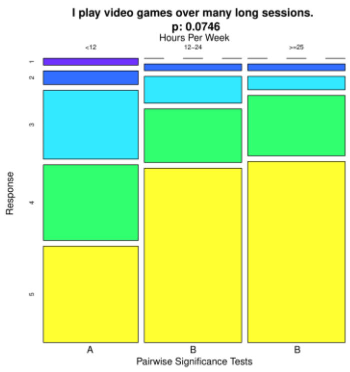
Figure 4. Responses 1 (Strongly Disagree) to 5 (Strongly Agree) to the statement “A lot of my free time is spent playing video games”

Table 3. Top five codes (based on All category) discovered in free form feedback. Columns represent All participants, then participants self-labeled as Casual, Intermediate, and Expert. Items more frequent than 25% are marked with *

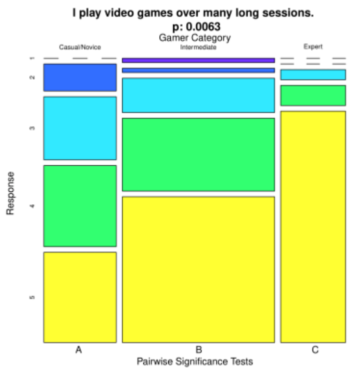
	All	Casual	Intermediate	Expert
Time Spent Playing	*0.371	*0.519	*0.344	*0.308
Skill	*0.328	*0.260	*0.360	*0.346
Knowledge	0.207	0.148	0.213	*0.269
Years Spent Playing	0.164	0.037	0.098	*0.462
Variety of Genres Played	0.112	0.074	0.131	0.115



(a) Compared to hours per week



(b) Compared to percentile hours per week



(c) Compared to self-chosen gaming label

Figure 5. Responses 1 (Strongly Disagree) to 5 (Strongly Agree) to the statement “I play video games over many long sessions”

The most common theme mentioned when considering all categories was how often participants played video games, with 37% of all participants mentioning it. However, the breakdown changed when examining “Casual” versus “Intermediate” and “Expert”. Almost 52% of all casual participants cited their time spent playing, but only 34% of intermediate and 31% of expert participants. The most common code referenced by intermediate players was their skill at a game,with 36% of participants mentioning it, compared to 35% for experts and only 26% for casuals. The highest code for expert players was the number of years spent playing at 46%, compared to 10% for intermediate and only 3% of casual participants. The priority shift between casual and expert gamers shows that casual gamers consider how infrequently they play video games as their main deciding factor, while expert gamers place more emphasis on the number of years spent playing.

Figure 6 shows years spent playing as a percentage of the participant’s lifespan. The “Casual/Novice” category was not statistically significantly different from the other two, but “Intermediate” and “Expert” were significantly different. Participants picking the “Expert” label overwhelmingly had spent 75% or more of their life playing video games. No one in the “Expert” category had spent less than 50% of their life playing video games. The closest of the 15 factors related to this aspect would be number 14, “Time started playing games relative to the age of the industry”, for which Adams and Ip recommend the extremely low weighting of 2 out of 10.

5. DISCUSSION

5.1 Research Questions and Interpretation

Table 4. Pairwise statistically significant differences between Hours Per Week (HPW5, HPW3) groups or Self-Chosen Gaming Labels (Labels). Presence of * in Sig. columns represent a pairwise p-value significance. Weight is from Adams and Ip (2002)

Factor	Weight	Sig. HPW5	Sig. HPW3	Sig. Labels
Play games over many long sessions	10	*	*	*
Discuss games with friends/bulletin boards	10			
Comparative knowledge of the industry	10			*
Much more tolerant of frustration	9			
Desire to modify or extend games in a creative way	8			
Technologically savvy	7			*
Have the latest high-end computers/consoles	7			*
Hunger for gaming-related information	6			*
Engaged in competition with themselves, the game, and other players	6			
Willingness to pay	5			
Prefer games that have depth and complexity	3			
Prefer violent/action games	1			

Table 1 shows that there is no consensus for hours per week as a metric for defining demographics of gaming skill (**R1**). Exploration into hours per week as a metric showed that HPW did have statistical significance with factors explicitly referencing the time spent playing video games, Figures 4 and 5, and nothing else (**R2**). A self-chosen gaming label has more reliable significance (**R3**, **R4**) as seen in Figures 1 through 5.

When ordering the factors from our code book from most frequently mentioned to least frequently mentioned, time spent playing, skill, knowledge, and years spent playing are the four most frequently mentioned factors (Table 4). Out of these four, only knowledge was given the highest weighting of 10 by Adams and Ip (2002). Years spent playing, which can be used to measure the factor “Time started playing games relative to the age of the industry”, was given the extremely low weight of 2. However, Years spent playing is shown to have extremely high importance to expert gamers (Table 4) and is statistically significantly related to participants who selected the “Expert” label (Figure 6). The suggested weights from Adams and Ip (2002) are not accurate to gamer’s perception of their labels and which factors are considered internally to make the decision between labels.

5.2 Future Work and Limitations

Some of these factors can build to a gamer skill demographic or categorization useful for academia, but more specific testing is required. We intend to continue this work to define a binary category (gamer/not gamer) as well as a nonlinear gamer skill demographic framework for gamer archetypes. The concept labeled as “Expert” varies meaning between research, meaning anywhere from “familiarity with gaming in general” to “spends a lot of time playing video games”. By applying standard HCI survey validation techniques to the 15 factors from Adams and Ip a standardized weighting and resulting demographic categories can be obtained.

The factors collected in this study creates a large multivariate data set. Contingency tables are only as powerful as how two factors interact with each other. Clustering is another statistical analysis tool for detecting associated factors. Future work will use nonparametric clustering to begin the framework for gaming demographic archetypes.

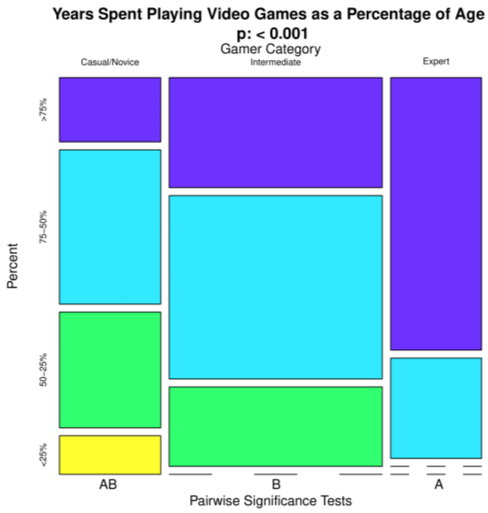


Figure 6. Years spent playing video games scaled as a percentage of the participant’s reported age

Additionally, individual researchers may have specific reasoning relevant to their own research subjects for which a one-off definition for gamer skill categories is necessary. We caution against this as it leads to confusion if the common terms of "Expert", "Novice", etc. are used. It would be more beneficial if researchers make note of the context in which their definitions apply.

Finally, the suggested metric of self-chosen gaming labels is one of a subjective measurement. When using subjective self-reporting measurements, researchers should keep in mind the characteristics of the participants and how they might affect the metric. Despite the subjectivity, however, our work has shown the metric to be reliable and statistically significant with many factors.

5.3 Conclusion

Table 1 shows that there is no consensus for hours per week as a metric for defining demographics of gaming skill. While hours per week does have statistical significance with some factors, a self-chosen gaming label has more reliable significance. The 15 factors from Adams and Ip (2002) are promising, but there was no experimental data examining the validity of their factors. Adams and Ip indicated that you can weight each factor arbitrarily according to the perceived importance by the game marketer. But this did not create a standard for comparison with other studies.

Despite being a subjective label, requesting participants to provide their own evaluation of their gamer seems to capture a measurement of the participant's mindset that is significantly associated with many of the responses in our survey. Conversely, hours per week was mostly independent of the survey responses. In fact, there was no response category associated with hours per week that was not also associated with the self-chosen gaming label. Hours per week may capture the idea, but a self-chosen gaming label appears to be the stronger metric.

While clustering is intended to be utilized in future work to examine nonlinear gaming demographic categorization, self-chosen gamer level appears to be a more predictive category than hours per week. We recommend that hours per week should only be used in the context of previous familiarity with video games, not as a generalization of expert/non-expert demographics. Based on our results, the three self-chosen gamer labels (Casual/Novice, Intermediate, and Expert) can be a good choice for researchers. It not only captured the same idea across research topics but could be used to predict many other factors. Researchers, when given the choice to pick between asking one question versus 15, when both options capture the same complexity, the shorter survey should be chosen.

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