Gamification Archetypes Validation for Energy Applications

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Abstract

Understanding consumer behavior in various energy applications such as transactive energy systems requires modeling user archetypes. Previous efforts to identify these archetypes have been based on gamification. This paper evaluates potential new consumer archetypes specifically designed for energy applications. We identify an archetype that is different from conventional gamification models and validate it using online survey tools in anticipation of its implementation on a distributed energy resource agreement platform. The methodology for validating the archetypes is described and the results of surveys in the USA are presented.

Keywords: gamification, transactive energy, consumer archetypes

1. Introduction

In many instances, a technologically sophisticated product that caters to user needs may not resonate as expected with the intended audience. This highlights the crucial role of user research in product development, as a high-quality product not only prioritizes features but also places human cognition at the focal point to ensure users receive what they intend from the product. Research including uncovering the users' concerns, expectations, and limitations captures important observations that add value to the product lifecycle management. These insights from users significantly influence the design decisions, directly impacting the user experience, which ultimately determines the longevity of the product. A tool model is necessary to assist researchers in identifying user behavior, especially the users' motivations and intentions.

In the digital era nearly everything is being analyzed and quantified, including the dynamics between humans, machines, and systems. When Nick Pelling formally introduced the term 'gamification' back in 2002, it became a hot topic, with many trying to align their products or services to improve user engagement (Cloke, 2019). Unlike fully developed games, however, gamification is a game dynamic model adopted to enhance user experience and engagement in non-game contexts (Deterding et al., 2011). This concept, which integrates game design elements into non-game contexts to model engagement has since become a significant aspect of various fields.

In 1996, Richard Bartle outlined four distinct player types comprising online gaming communities, each displaying unique behaviors and motivations. While individuals may exhibit aspects of all four types, one archetype typically dominates their overall gaming style (Bartle, 1996b). Bartle's introduction of the taxonomy of player types: *Killer*, *Socializer*, *Achiever*, and *Explorer* has become a valuable reference for various industries, extending beyond gaming into non-game environments. However, his theory can appear vague in other domains, especially with the suggestion that the majority of players exhibit socializing tendencies.

To investigate whether people generally fall into the 'socializer' category as they do in gaming settings, as Bartle suggested, it is essential to consider analyses beyond gaming contexts. This paper aims to determine whether 'The Bartle Test of Gamer Psychology' is a valid model for identifying personality types in non-game domains, such as energy, and to explore how modifications to Bartle's taxonomy in

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these contexts could help achieve policy goals(Bartle, 1996a). Additionally, the research seeks to develop a comprehensive archetype model for energy consumers, focusing on gamifying products or services to enhance user engagement.

2. Literature Review

Bartle's exploration of Multi-User Dungeons provides a quiz enabling researchers and game designers to identify the user's tendencies in gaming environments with 4 distinct player types: Achiever, Explorer, Socializer, and Killer. As Bartle pointed out, the equilibrium of all four personalities does not suggest that every player embodies just one personality type. Instead, it signifies that the proportions of these personalities remain stable over time. The questionnaires were crafted to present choices in a "This or That" format, prompting Yee to reconsider the questionnaire's validity due to its lack of empirical testing (Yee, 2006). Yee also pointed out that Bartle's four player types may exhibit high correlations with each other, indicating potential ambiguity in the results.

Bartle's work inspired Yee, a consultant specialized in game analytics to explore his research approach further, leading him to develop an empirical method for understanding players' motivations in online games. Yee's questionnaire, 40 questions featuring five labeled scale points for responses, was distributed to 3000 Massively Multiplayer Online Role Playing Games (MMORPG) players, enabling a more focused analysis of the results. The analysis portrayed diversity and showcased a wider array of motivational patterns among the players as compared to Bartle's four player types. For example, Yee included new motivations - Escapism and Customization under the category of Immersion that were never discussed by Bartle. Yee also argued that there exists overlap between Bartle's proposed achiever and killer player types, suggesting they should not be deemed as distinct categories; in results, the two were merged under the same umbrella of Achievement as "Mechanics" and "Competition".

The authors of "Player Typology in Theory and Practice" suggested that methodologies by Bartle or Yee are primarily applicable to massive multiplayer games and should be viewed as general ideas only (Bateman et al., 2011). Consequently, they argued that a narrower context is necessary to gain a deeper understanding of players. Hence, they recommended that typologies should focus on identifying patterns within the data rather than confirming preconceived notions. Two years later, the authors unveiled an interim model called "BrainHex," merging prior discoveries from player research with neurobiological insights into the hypothesized underlying mechanisms (Nacke et al., 2013). BrainHex presents seven archetypes: Achiever, Conqueror, Daredevil, Mastermind, Seeker, Socializer, and Survivor, and assesses them according to the Myers-Briggs Type Indicator (MBTI) schema. The model provides a broader spectrum of insights into players' behaviors, going beyond the typical typology to encompass the players' cognition as well. It does so by considering not only playing skills but also aesthetic experiences, interpersonal relationships, comedic or dramatic elements, social interactions, goal-completion, and long-term achievements.

Gamification serves the purpose of providing entertainment in non-game contexts, aimed at addressing, resolving, and creating engagement through challenges, goals, rules, feedback, interactions, narratives, uncertainties, social interactions, and rewards (Salen and Zimmerman, 2004). In light of this, various fields such as employee training, education, and marketing adopt gamification to cultivate engagement. For example, distributed energy resource aggregation companies such as Ohmconnect introduce an interesting energy business concept–enabling residential clients to engage in the power system market through a mobile application (OhmConnect, 2024). The company strategically incorporates gamification into the system with features such as point rewards and frequent notifications regarding price and performance updates, resulting in claims that users save \$300 to \$500 annually (Sioshansi, 2021). However, studies show that the error rate in estimating load consumption can reach as high as 50% because customers are hesitant to grant aggregators full control over their associated assets (Weng et al., 2017). This highlights the importance of understanding the users including their behaviors, habits, preferences, and pain points are essential to enhancing user engagement. Other than that, it is also important to refine regulations and policies, particularly within the energy sector, to align business model structures with long-term sustainable goals. The current policy framework predominantly prioritizes technological viability, neglecting broader implications for businesses' sustainability over time (Burger and Luke, 2017). Given these concerns, policymakers are working to utilize gaming within governance to enhance policy planning and organizational decision-making Geurts et al., 2007).

Gamification inspired approach to employ peer comparisons in retail electricity context was studied with laboratory economics experiments (Baltaduonis et al., 2022), which produced mixed results for its impact on the efficiency outcomes. However, an interesting insight was that the participant endorsement for institutional regimes providing peer comparison information dwindled after experiencing the approach in action. Thus, misapplied gamification approaches can compromise the roll-outs and public support for new programs, policies and regulatory environments.

3. Methodology

The literature review revealed that the grouping of individuals into archetypes in a gaming context can be better aligned to the domain. This can be achieved by expanding the questionnaire's scope to cover a broader array of topics, providing more diverse options instead of binary choices. Furthermore, addressing the correlations between the archetypes is essential to avoid enigmatic or irreproducible results. While archetypes proposed by researchers have been widely adopted for various purposes, it is imperative to focus on crafting archetype patterns rooted in well-founded data rather than solely verifying the validity of models proposed by others. With that said, a more in-depth study of archetypes is needed, particularly in non-game domains such as energy consumption, as they are extensively employed by various industries, including policymakers and product designers, not only to enhance user engagement but also to improve business models and operating paradigms.

3.1. Design and Procedures

To create an archetype model applicable to more broader energy consumer domains, the questionnaire was crafted for distribution to participants across the United States, aged 18 and above, using the Prolific survey platform. Unlike Yee's exclusive focus on MMORPG players for his research study, our survey was not specifically targeted towards any particular group (Yee, 2006). The questions are designed to be universally comprehensible and relatable, diverging from Bartle's narrow focus on gaming contexts when identifying player types. Consequently, the model created for this paper changes the terminology from "player" to "participant," as the model is intended for a more generic environment beyond gaming. The approach we propose comprises two validation dimensions: one internal, which centers on validating participants' archetypes using their own choices, and external, involving a group of 100 respondents who assess the relevance of the questions and options for the four proposed archetypes: Achiever, Explorer, Socializer, and Influencer, as shown in Figure 1.

Before distributing surveys to the participants, an external validation test is conducted with 100 validators

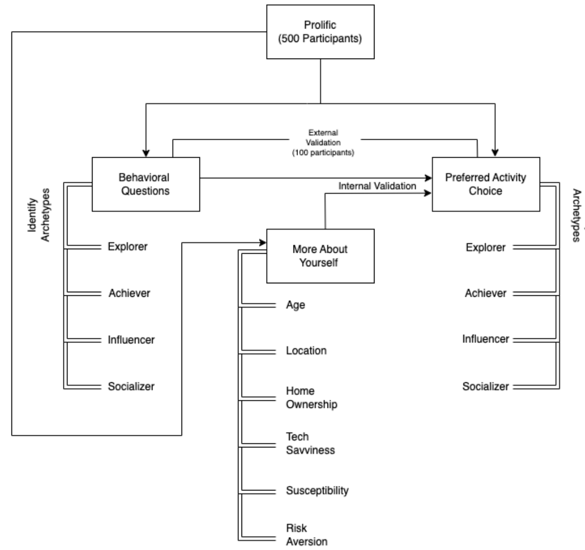

Figure 1. Survey Plan

via Prolific. This aims to assess the relevance of the questions and options for the four proposed archetypes: Achiever, Explorer, Socializer, and Influencer. As suggested by the Delphi method, achieving a median threshold of 75% agreement among validators indicates high relevance between the archetypes and the designed options for the questions (Barrios et al., 2021). 81.25% of the questions achieved 75% or higher agreement among validators and the lowest percentage of agreement is provided for the answers chosen for use.

Once the external validation finalized the 8 behavioral questions, the researchers combined 23 questions, which comprised 8 behavioral questions, 1 question about the preferred activity (for internal validation purposes), 12 additional questions about themselves, and 2 identity validation questions. The 8 behavioral questions cover various everyday scenarios such as fitness, concerts, gaming, dining out, credit cards, and event planning, avoiding solely on gaming context. These questions are designed to pinpoint participants' archetypes.

Following this, the preferred activity question is designed for internal validation purposes to confirm whether the identified archetypes from the behavioral questions align with the chosen activities, each of which relates to distinct archetypes. The preferred activity question was designed to determine whether participants' archetypes are predictable through their preferred action, as shown in Figure 2.

Additionally, the survey also includes 12 more 'about yourself' questions focused on various personal characteristics such as susceptibility, risk aversion, tech-savviness, location, age group, and

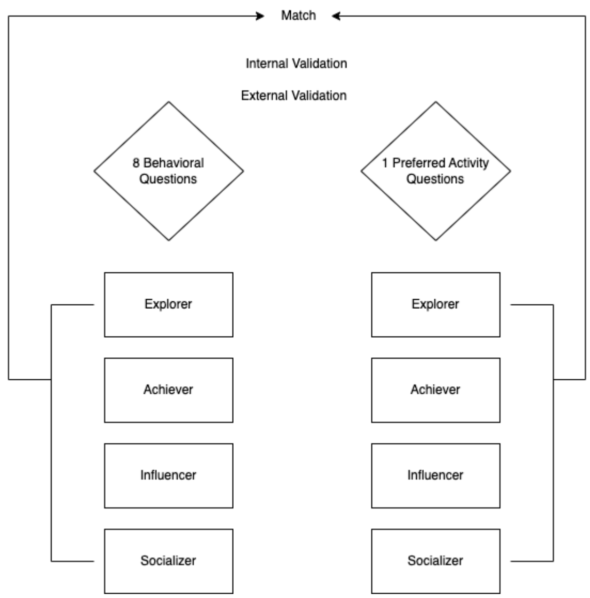

Figure 2. Verify the identified archetypes resulting from behavioral questions with the activities selected (where each activity relates to a specific archetype)

homeownership. These questions are designed to gather participants' demographic information and complement it with identified archetypes for relevance assessment. Likert scales are employed to measure both risk aversion and tech-savviness levels. The general risk question enables participants to assess their willingness to take risks on a scale from 0 (not willing) to 10 (very willing) as proposed by authors that studies risk attitudes (Dohmen et al., 2011). Sudzina's proposed tech-savviness measure is evaluated on a scale from 0 (strongly disagree) to 5 (strongly agree), incorporating self-perception and external opinions on technological proficiency (Cecilia et al., 2017). Furthermore, the survey also integrates the Pew Digital Savviness (PDS) Classifier through multiple-choice questionnaires to determine internet usage frequency and individuals' confidence in using electronic devices for online tasks (Center, 2018).

When addressing susceptibility, belief elicitation exercises utilize phrases like 'do you think' or 'would you try' to assess participants' susceptibility levels. These exercises offer four response options: 'definitely yes,' 'probably yes,' 'probably not,' and 'definitely not' (Phan et al., 2023). Additionally, age groups are categorized as Silent, Boomers, Gen X, Early Millennials, Late Millennials, and Gen Z for analytical purposes, as well as collecting their location information. Homeownership status is determined by whether participants rent, own a home, or others where

Group (count)	Median Time (min)		Payment
	Estimated	Actual	Rate ($/h)
Participants (500)	10	4.28	16.00
Validators (100)	30	7.74	16.00

Table 1. Estimated and actual completion times for participants and validators

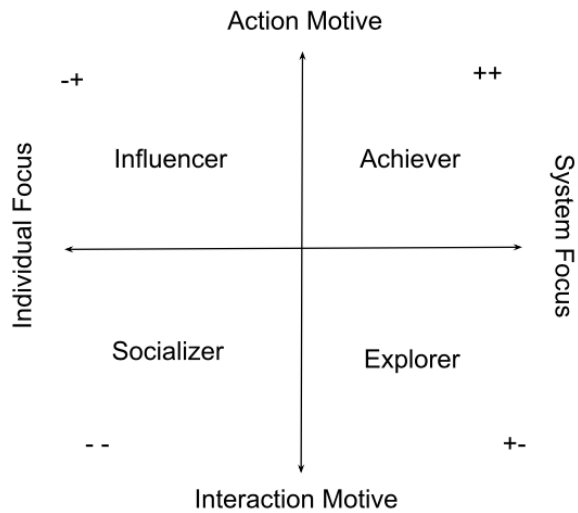

Figure 3. The data allocation graph inspired by Bartle's interest graph

they are allowed to explain it in words. The final 2 questions aimed at identifying bots and verifying participants from Prolific for payment purposes.

3.2. Data Collection

QuestionPro served as the primary survey tool for both validators and participants, and the survey is distributed via the third-party survey recruitment platform, Prolific. The settings in Prolific are set to distribute the survey all across the United States only, with equal distribution to males and females. However, the payment between participants and validators is different due to the estimated median time of completion, as shown in Table 1.

Participants and validators who successfully provide their Prolific ID at the end of the survey and enter the designated code into their Prolific account as proof of completion will receive payment from the organization. The 500 recruited participants are also set to complete the survey at various times, split across two different days and three different time slots: Wednesday at 8 AM, 12 PM, and 4 PM PST, and Saturday at 12 PM PST.

3.3. Data Allocation

The partition shown in Figure 3 displays the x-axis representing the shift from individual focus to system focus, and the y-axis representing the tendency towards action motive or interaction motive. The participant's attention is represented on the x-axis, with system focus depicted as positive and individual focus as negative. It is important to note that no comments are made on the portrayal of characteristics as positive or negative values. Similarly, the motivation is depicted on the y-axis, with the action motive represented on the positive side and the interaction motive on the negative side. Using these axes, quadrants are formed, categorizing participants into one of four types (refer Figure 3): Achiever (++), Influencer (-+), Socializer (–), and Explorer (+-). Both simple average as well as the weighted average are computed based on expert weights assigned to each answer type to determine the locus point of a participant's answers. The individual loci were determined based on the eight behavioral responses, which were either equally weighted or according to the validators' weights. Each response provides a score of +1 or -1 in two dimensions, which are then averaged to determine the individual locus.

3.4. Data Re-evaluation

To assess the consistency of the collected data, we resend the same questionnaire to the participants who originally completed the survey. The resend process follows the same timing as before. This process aimed to observe changes in the participant's responses over the past two months by comparing their answer selections between the two surveys.

4. Hypotheses

The research is testing the following hypotheses:

1. An individual's personality type can be determined from self-reported data about themselves;

2. An individual's personality type can predict their choices; and

3. An individual's personality type corresponds to an archetype that is stable over time.

5. Results

5.1. Survey Analysis and Correlation

The model with or without the validators' weight in Figure 4 shows that the recruited participants lean

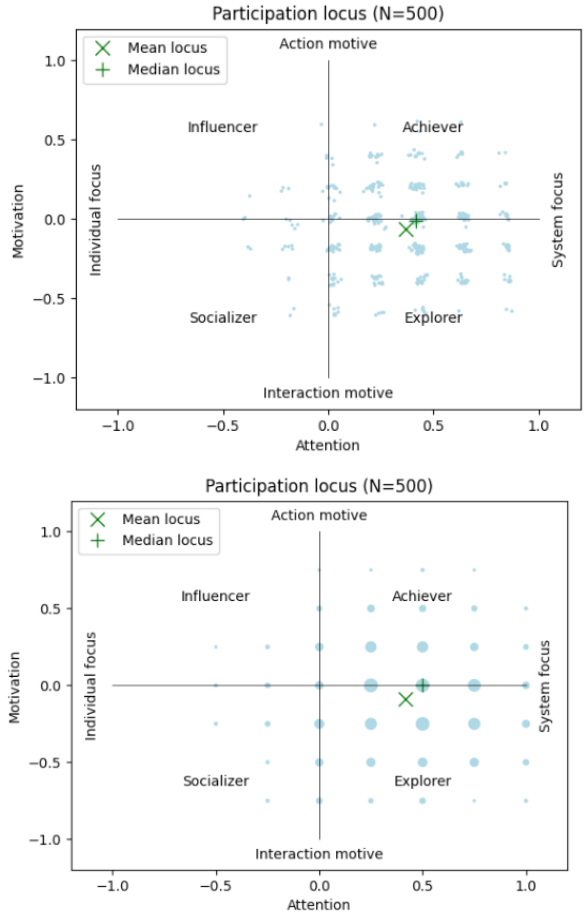

Figure 4. Participant locus with (top) and without (bottom) validators' weight

towards achiever and explorer types with a system-focus and a slight interaction motive. This significantly differs from Bartle's observation that the majority of players exhibit socializing tendencies, which suggests that Bartle's theory and the gamefication approaches based on it are not necessarily more broadly applicable in other fields. Table 2 shows the tech savviness dimensions are illustrated as follows: (1) "Other," which refers to how others perceive your tech savviness; (2) "Internet," which refers to how frequently you use the internet; (3) "Device," which refers to how confident you feel using computers, smartphones, or other electronic devices to accomplish tasks online; and (4) "Self," which refers to how you perceive your own tech savviness. Meanwhile, Table 4 explains susceptibility as follows: (1) "Friends," which refers to how easily you are influenced by your friends when making decisions; (2) "Next Year," which refers to whether you think you would enroll in an electricity-saving program next year; (3) "Soon," which refers to whether you think you would

Savviness Dimension	Correlation
Other & Internet	0.17
Self & Internet	0.16
Internet & Device	0.19
Self & Device	0.30
Other & Device	0.33
Other & Self	0.92

Table 2. Correlations between different tech savviness(Cecilia et al., 2017)(Center, 2018)

Motive-Focus Dimension	Correlation
Action & Interaction	0.08
Individual & System	0.09

Table 3. Correlations between action vs interaction and individual vs system

Susceptibility Dimension	Correlation
Friends & Next Year	0.55
Friends & Soon	0.56
Friends & Future	0.60
Future & Soon	0.67
Future & Next Year	0.67
Soon & Next Year	0.83

Table 4. Correlations between different susceptibility(Phan et al., 2023)

enroll in an electricity-saving program soon; and (4) ”Future,” which refers to whether you think you would enroll in an electricity-saving program in the future.

Tables 2, 3, and 4 show the correlation between the variables obtained from the ‘more about yourself’ section. Table 2 shows that the correlations within tech savviness are relatively weak, except for the variables of other savviness and self savviness, which show a strong positive correlation of 0.92. With that being said, there is a slight tendency for people who believe they are savvy on the internet to be device savvy as well. The same can be said for ‘Self Savviness’ – people who viewed themselves as tech savvy also believed they are actually savvy on the internet or devices. Nonetheless, the results suggest that other people’s perceptions of one’s tech savvy has a slight tendency to match with whether you believe you are savvy with the internet and devices. Lastly, how other people’s perceptions on your tech savviness holds a strong positive correlation which means as ‘Other Savviness’ increases, ‘Self Savviness’ increases too.

5.2. Survey Re-evaluation Analysis

The data collected from the re-evaluation after two months showed changes in the answer selections at the individual level between the two surveys. However, the shift in re-evaluation sample locus does not appear to be significant, with the locus remaining almost the same between achievers and explorers. This result does not reject the hypothesis that archetypes are stable over time in aggregate (refer Figure 5).

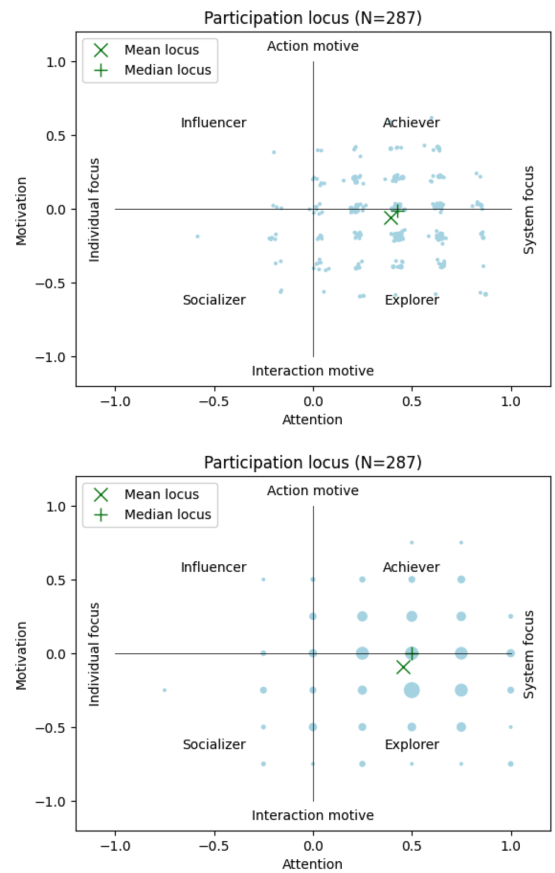

Figure 5. Participant re-evaluation data with (top) and without (bottom) validators’ weight

5.3. Regression Analysis

The collected data is analysed with a multinomial logistic regression, where the dependant variable is individual’s choice and explanatory variables are their personality type (determined with simple averaging of the behavioral answers), demographic and other individual characteristics, as presented in Figure 1.

The regression analysis does not reject the hypothesis that an individual’s personality type can help predict actions corresponding to that type. The highest likelihood of matches between personality types and actions was captured for choices that aligned with the archetypes. However, the results for the socializer

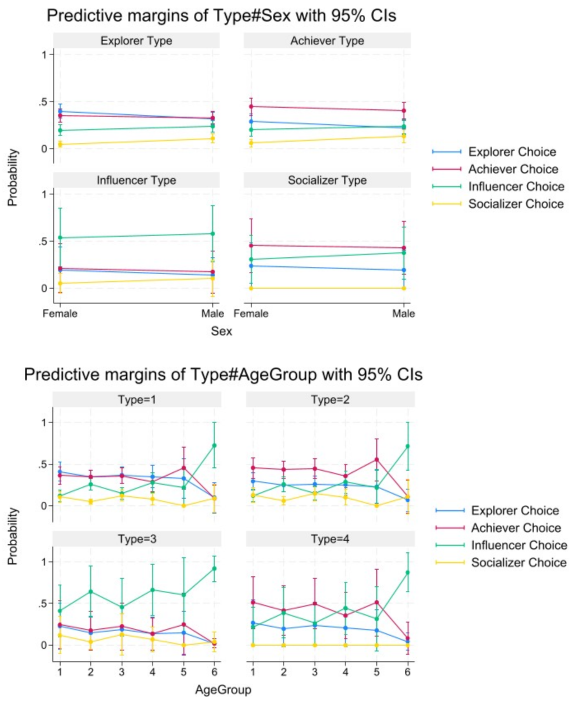

Figure 6. Regression results capturing tendencies of the personality types to predict the choices given specific sex and age group categories. Age Groups: 1-GenZ, 2-Millennial, 3-GenX-Young, 4-GenX-Old, 5-Baby Boomer, 6-Silent

Action Type	Personality Type Explorer	 Achiever	 Influencer	 Socializer
Explorer	**0.36** (0.00)	0.25 (0.00)	0.16 (0.12)	0.22 (0.05)
Achiever	0.34 (0.00)	**0.42** (0.00)	0.19 (0.11)	**0.44** (0.00)
Influencer	0.21 (0.00)	0.21 (0.00)	**0.56** (0.00)	0.34 (0.10)
Socializer	0.08 (0.00)	0.09 (0.00)	0.07 (0.30)	0.00 (0.99)

Table 5. Regression results that capture the predictive margin of the action choices given the personality type (dominant is bold and statistically insignificant is in red with p-values provided under each estimate)

archetype failed to produce significant results. The weaker socializer results might be due to the low number of socializer types in the participant pool as shown in Figure 6 as well as due to challenges of creating an enticing social activity in a survey format.

The researchers observed possible shared traits between the explorers and achievers, as the results showed an overlap for the corresponding action choices under the explorer type section when controlling for both age group and sex (refer to Figure 6. This suggests that during exploration, individuals may transition into achievers. Interestingly, significant action ordering patterns were evident under the achiever and influencer sections, with most individuals choosing options consistent with the related archetypes. However, such results were not observed for participants in the socializer category. The researchers speculate that this phenomenon may be due to the challenges to create strongly dominant choice for socializers via a survey. Therefore, given that individuals entail some traits of other archetypes, they ended up choosing actions that appeal to them more given the provided list, as shown in Figure 6.

The regression analysis also suggested that, aside from age group, the other individual specific data collected — such as susceptibility, risk aversion, home ownership, tech savviness and sex — cannot explain the choices under the defined archetypes.

Hypothesis 1	
Age	Consistent [see Note 1]
Sex	Rejected
Tech savviness	Rejected
Susceptibility	Rejected
Home-ownership	Rejected
Risk-averseness	Rejected
Hypothesis 2	
Archetype choice	Consistent
Hypothesis 3	
Archetype stability	Consistent [see Note 2]

Table 6. Hypothesis Testing Results

6. Conclusions

The principal results of testing our hypotheses are summarized in Table 6. We note the following regarding Hypothesis 1.

Note 1 Age is a significant explanatory variable for some archetyped choices with the older age groups standing out the most.

Note 2 Archetype stability is not fully consistent at the individual level but it is remarkably consistent in the aggregate.

The potential shortcomings identified in this study that require further investigation relate to sampling bias originating from Prolific, a third-party survey recruitment platform that enlists survey participants globally. There may be a notable inclination for recruited participants to exhibit traits of exploration and achievement, primarily due to the necessity for individuals to be accepted into the Prolific survey pool first, indicating early exploration with the platform and active involvement in survey participation. Participants who are motivated by financial gain are consistently attentive to survey notifications and readily participate in surveys for which they qualify. These aspects may influence that the final results are more likely to reflect characteristics associated with exploration and achievement, indicating a bias towards system-focused behaviors.

This motivates the research to proceed to the next step, validating the model through various other tools and channels. For instance, distributing the survey not only via new media but also through traditional channels like mail with a larger sample size that ensures diversity.

The participation incentive has also been identified as a potential shortcoming in this study. Although re-evaluation of the data has confirmed that participants consistently fall between achiever and explorer, the researchers are interested in assessing the accuracy of the data collected, particularly given the possibility that some participants choose answers randomly on paid survey platforms like Prolific. Since participants get paid upon survey completion, this does not assure data quality. Therefore, the researchers are considering adapting the incentivized research tools such as those used in experimental economics to motivate participants to be more attentive to the assigned tasks or surveys and complete them more thoroughly.

The next phase will focus on refining the methodology for conducting incentivized surveys or experiments targeting the energy sector, aiming to understand participant archetypes and behaviors related to energy consumption. The participant recruitment process will need to be more diverse compared to the current version to minimize sampling biases, provide stronger support for the conclusions, and aid in product design and policy implications. Additionally, the researchers are also interested in incorporating latent (anti-social) behavior into this model to understand how participants engage in general electricity usage when incentives are involved.

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Addendum

The following is the questionnaire given to participants.

Hello,

We are interested in distinguishing between participant types based on survey questions. You are required to answer all questions.

Thank you for your time!

Note: There are no correct or incorrect answers

Behavioral Questions

You're one step away from reaching the next level in an online game. What do you believe would accelerate your progress towards that goal?

1. Pursuing higher rankings for better rewards
2. Venturing into a new map in the game
3. Collaborating with fellow players in a team
4. Broadcasting my narrated gameplay

What approach would you consider to earn a free smartwatch from the fitness program organized by your community?

1. To join a fitness group to meet new people
2. To try a bootcamp with different fitness classes
3. To engage in daily workouts to advance in the fitness program
4. To recruit more members to join the fitness program

Your favorite restaurant is offering a giveaway , which of the following activities would you be willing to do in order to receive the giveaway?

1. To rate and review the food online
2. To beat the food eating challenge
3. To try different dishes on the seasonal menu
4. To bring a friend to dine in together

When playing board games with your friends, which of the following options best describes your strategy?

1. I learn the game rules as you go
2. I cooperate with other players as much as possible
3. I dominate the board
4. I convince other players to adopt new rules for the game

You participate in a lottery to win a pair of concert tickets featuring a popular band. What are you willing to do to win the tickets?

1. I would share organizer's post on your social media
2. I would listen to the band's music from different time periods
3. I would join the fanbase group online
4. I would pass the band's loyalty quiz

When engaging in a new game for the very first time, which of the following options best reflects your approach to playing?

1. I navigate the game by trial and error
2. I share suggestions how to play the game
3. I aim to advance to the next level first
4. I befriend other players to learn and make connections

When looking for a credit card, which of the following factors holds the highest importance to you?

1. An option to encourage businesses to adopt the card
2. New and unique features of the card
3. Highest cashback on purchases
4. Ability to easily split bills with others

When coordinating an event, what matters most to you?

1. That it is a sold-out event
2. That it connects people
3. That it attracts new participants
4. That it is a new experience

More about yourself

Overall, how often do you use the internet?

1. Never
2. Less than once a week
3. Once a week

4. Several times a week
5. At least once a day
6. Multiple times a day
7. Most of the day

Overall, how confident do you feel using computers, smartphones, or other electronic devices to do the things you need to do online?

1. Not at all confident
2. Only a little confident
3. Somewhat confident
4. Very confident

How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

How would you rate yourself from scale 0 (not willing to take risks) – 10 (very willing to take risks)

Do you think you will enroll in an electricity saving program soon?

1. Definitely yes
2. Probably yes
3. Probably not
4. Definitely not

Do you think that you will enroll in an electricity saving program next year?

1. Definitely yes
2. Probably yes
3. Probably not
4. Definitely not

Do you think that in the future you might enroll in an electricity saving program?

1. Definitely yes
2. Probably yes
3. Probably not
4. Definitely not

If one of your best friends were to convince you to enroll in an electricity saving program, would you give it a try?

1. Definitely yes
2. Probably yes
3. Probably not
4. Definitely not

People consider me to be tech savvy

How would you rate yourself from scale 0 (strongly disagree) – 5 (strongly agree)

I consider myself to be tech savvy

How would you rate yourself from scale 0 (strongly disagree) – 5 (strongly agree)

Do you rent or own your home?

1. I am a homeowner
2. I am a renter
3. Other:

What is your age group?

1. 18 to 24
2. 25 to 34
3. 35 to 44
4. 45 to 54
5. 55 to 64
6. 65 or over

What state do you live in?

Choose one from the 51 states in the United States including the District of Columbia

Preferred Activity

Choose your preferred activity from the list below

1. I choose to read the press release to learn about the largest camera in the world
2. I choose to compare your completion time of the survey with others
3. I choose to provide rating and feedback regarding the survey
4. I choose to connect with us on social media

Please copy & enter code - C1G28VZ5 to your Prolific portal to prove that you have completed your survey.

Please enter your Prolific ID below:

Select Captcha and Verify