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App Usage Patterns in the Platform Economy: An Exploratory Study on Sustainable Digital Ecosystems and Device Possession

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Abstract

In the context of the platform economy, this study preliminarily examines how smart device possession affects the sustainability of app usage behavior. This research analyzes app usage as a core component of value creation within a sustainable digital ecosystem. As an exploratory pilot study serving as a proof of concept, we focus on how different ownership patterns influence digital consumption performance, categorizing users based on three dimensions: the number of devices owned, screen size (portability), and inter-device compatibility. Furthermore, the study elucidates how device relationships affect engagement across app categories, investigating whether devices function as primary, complementary, or independent tools. By analyzing these exploratory behaviors, the research offers insights into multi-device usage patterns for a more efficient digital experience while reducing resource redundancy. Ultimately, these findings provide practical guidance for fostering a more balanced and resource-efficient digital society.

Keywords: sustainable digital ecosystem; platform economy; app usage behavior; value creation; device repertoire; task–technology fit

1. Introduction

Recent data show that more than 45 million people in South Korea use smartphones [1]. Except for infants and children who are unable to use smartphones, most Koreans are using smartphones in Korea considering the nation's total population is about 50 million. At the same time, the number of Tablet PC users such as iPad and Galaxy Tab have also been increasing exponentially. Current market trends show that consumers increasingly utilize multiple smart devices, with attributes such as portability and screen size shaping distinct usage patterns [2]. Similarly, recent research indicates that the expansion of mobile device usage has fostered complex interaction patterns where users switch between devices based on their perceived self-efficacy and information-seeking needs [3]. As smart devices have come deep into our lives and are now indispensable, the app market has also grown tremendously. Recent global market indicators confirm that multi-device ecosystems and fragmented platform connectivity have become the baseline for modern digital consumers, accelerating the fluidity of daily app usage across different hardware forms [4,5]. Integrating these recent dynamics allows this study to effectively bridge classic behavioral frameworks with the current state of the platform ecosystem.

With the rapid acceleration of the platform economy, the proliferation of multiple smart devices—such as smartphones and Tablet PCs—has fundamentally transformed users' digital consumption behaviors. However, while the existing literature has extensively examined single-device usage, the complex dynamics of multi-device portfolios remain



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underexplored, particularly concerning their impact on digital sustainability [6]. In the context of the modern digital ecosystem, sustainable consumption is not merely about physical energy efficiency, but also critically encompasses ‘social sustainability.’ This includes optimizing user attention, maximizing digital well-being, and minimizing the redundancy of technological resources across devices [7]. Therefore, understanding how specific device attributes—such as screen portability and OS compatibility—dictate app genre selection is a fundamental prerequisite for fostering a balanced and resource-efficient digital environment.

The use of most smart devices is convenient because they are completed through a variety of apps. Therefore, we conducted this study in order to analyze app usage behaviors through the classification of smart device possession. Since there are diverse smart devices and apps, the question may arise: ‘Wouldn’t the trend of using apps vary depending on what smart devices you have?’ When it comes to a computer, the overall usage behavior, such as the purpose and frequency of the devices, depends on their performance, size and portability [8]. Similarly, in the case of smart devices, each person has a different situation in their smart device possession and it will certainly affect people’s use of smart devices, consequently changing app usage behaviors [9]. Therefore, we would like to study with a prominent theme in mind: ‘App usage behaviors will vary depending on the characteristics smart devices’. However, if you have more than one smart devices, the relationship between the devices would become important. One is mainly used and the other may play a complementary role in the use of the device, each of which can be used with a distinct purpose or may be used individually without having any significant impact on each other.

Therefore, this study focuses on the relationship between devices while considering app usage behavior based on the number of devices, the size of the device’s screen (associated with portability), and the level of compatibility between the devices. In other words, we try to categorize the characteristics of smart device users and figure out how the situation of device possession differs in the level of particular genre of app usage. This study transcends a simple analysis of device usage; it explores the ‘Sustainable Digital Ecosystem’ by identifying how the configuration of a user’s device repertoire influences the quality of digital consumption. By examining the synergy between hardware specifications and software genres, this research aims to provide a blueprint for minimizing resource redundancy and enhancing digital well-being in an increasingly fragmented device landscape.

2. Literature Review

The digital ecosystem is currently transitioning from a smartphone-centric model to a diversified multi-device paradigm. Despite a segment of the population maintaining single-device usage, an increasing number of individuals now integrate supplementary smart devices into their daily routines. Such shifts in device possession have fundamentally transformed app engagement behaviors, necessitating a more nuanced understanding of the modern app market. The app market has grown quickly, and the way people use smart devices has become more diverse. However, there are few studies that closely examine app usage behavior based on smart devices.

As mentioned earlier in the introduction, this study divides three characteristics of smart devices possession in order to figure out the impact of users’ behavior of using apps. The first is the number of devices you have, the second is the size of the screen, and the third is the compatibility of the device’s software feature. There are not many studies on smart devices and content because it has not been long since a variety of mobile devices were used. However, even before the launch of smart devices, it has been revealed in studies that the screen size and the compatibility of electronic devices have an impact on

work efficiency and concentration. Therefore, we look at prior research related to three key independent variables in this study. At the same time, we also look at studies related to app classification in order to analyze changes in app usage behavior.

2.1. Action Theory

The overarching theory in this study is action theory. Action theory refers to a sociological approach that first appeared in Max Weber's book [10], "Economy and Society" (1924), emphasizing how people perceive social situations and goals they choose to pursue. In other words, actions should be interpreted in terms of subjective intended meaning in order to explain one act. One person's actions show that it should be explained in terms of the individual's intended purpose and that various purposes are compared and reviewed in using the appropriate means to obtain a given purpose. Based on the Action theory, the research was conducted by applying the sociological basis of Action theory on how users influence the usage characteristics of smart devices for the purpose of selecting and using apps.

2.2. Genre Repertory Theory

It is the "genre repertory theory" that consumers spend with a certain amount of their own repertory, rather than forming a random consumption pattern in consuming goods or content. As consumers tend to prefer only some specific genres of content and use it repeatedly, even in environments where content of various genres exists when consuming content, it has become increasingly important to classify and access the content consumption structure into genres [11,12]. This preference for only certain genres has been studied in many areas. For example, people generally spend a lot on certain brands of clothing, watch only a limited number of channels on TV, and use a limited number of apps on mobile devices. This category of genre is widely applied not only to actual goods but also to digital content aspects. In this study, we try to look at consumers' usage of app genres in smart devices. Apps that can be used on smart devices provide a variety of genres in app stores, Google Play, and Marketplace, providing an environment for consumers to decide from on their own. Despite the many choices available, consumers are expected to prefer and use certain genres of apps more repeatedly according to the genre repertory theory even in this environment [12].

2.3. Task–Technology Fit

To provide a comprehensive understanding of the transition from user intent to actual behavioral outcomes, this study integrates the Task–Technology Fit (TTF) framework [13]. At its core, TTF posits that the impact of information technology on individual performance is optimized only when the capabilities of the technology are aligned with the requirements of the task at hand. In the context of a multi-device ecosystem, 'technology' refers to the physical and functional attributes of smart devices—such as screen size, processing power, and OS compatibility—while 'tasks' are defined by the specific app genres (e.g., productivity, entertainment, or communication) within a user's genre repertoire [14]. The integration of TTF is particularly vital for analyzing 'sustainability' within digital ecosystems.

Sustainability is not merely achieved through the acquisition of high-specification hardware, but through the optimal calibration between device characteristics and usage patterns. For instance, while a large-screen tablet offers high visual immersion for entertainment tasks, its lack of portability may create a 'misfit' for mobile-centric activities, leading to inefficient resource utilization. Furthermore, the degree of inter-device compatibility acts as a critical moderator that determines whether a device functions as a primary tool or a redundant asset [15]. By applying the TTF lens, this research moves beyond descriptive

analysis to explain the underlying mechanisms of why certain device portfolios foster more stable and efficient app usage behaviors than others.

2.4. App Classification

Consumers can download or purchase apps on Apple's App Store and Google's Google Play, each offering between 2,100,000 and 3,600,000 apps. Each market provides app categories, and various institutions and research institutes divide app categories and conduct research. In various prior studies, researchers have classified the apps into categories in order to systematically examine consumers' behavior in using apps. According to the Korea Internet & Security Agency's survey of smartphone usage, the types of apps were divided into 15 categories and investigated app usage rankings by category. Google Play Store has 27 categories, and Apple App Store has 23 categories to offer to consumers. Lee et al. [12] used App Store's (Apple) category criteria to examine preferences in app categories according to smartphone acceptance and rejection. However, the above categories are based on the application's usage area, and there are studies that classify them according to the characteristics of the applications and grouped them into four or five categories. Alley & Gardiner [16] looked at the acceptance and productivity of smart devices by grouping users based on the app classifications of Education, Entertainment, Social Network, Productivity, and Business. Kim et al. [17] analyzed the factors that cause app purchasing decisions through four criteria: Productivity, Entertainment, Information, and Communication. In this study, we try to analyze consumers' usage behavior of apps by categorizing them according to the characteristics of the apps, and we adopt the classification criteria used in the study. The classification is shown in Table 1 below.

Table 1. App categorization [17].

Categorization	Appstore Classification	Criteria
Productivity	business/utility/productivity	Increase business efficiency or practical applications
Entertainment	game/sports/music/photography	Applications that focuses on interest and fun
Information	fnance/news/travel/books/education/medical/ weather/health and fitness/navigation/life style	Applications that provide information
Communication	social networking	Apps that provide seamless communication with people to build and maintain relationships

2.5. Device Possession

The combination of smart devices owned by users is becoming more diverse with the development of various types of smart devices. In the past, most users used only one smartphone, but with the advent of Tablet PCs, the number of smart devices owned by individuals is increasing. In particular, with the continuous launch of various screen-sized smart devices, users have more choices to choose from. Furthermore, smart devices are being used in various combinations related to work as well as for leisure activities [18]. Depending on the consumer's personal characteristics or purpose of use, the screen or type of smart device to be purchased will be different, and the use of apps through this device will be very different. From this perspective, it is necessary to figure out how smart devices will affect consumer behavior, especially the purchase or utilization of apps. In this regard, Hwang et al. [19] studied that the effects of having additional smart devices and large-screen smart devices on the purchase of digital content.

According to the study, additional purchases of smart devices change users' content purchasing patterns; the more devices they have, the less sensitive they are to the price of digital content and the greater the likelihood they are to be purchased. Moon & Yoon [20] also conducted a study on the adoption of the Tablet PC as an additional smart device. Results show that when users consider using Tablet PCs, usability

and playfulness are the most important factors, especially playfulness. This shows that the choice of additional smart devices may be the goal of entertainment.

2.6. Device Display Size

Few studies have been conducted on the relation between the screen size of smart devices and consumers' app usage behavior. But research on the impact of screen size on consumers has been steadily underway. Although the functions and performance of devices are almost identical, many devices have different shapes, particularly the size of the screen [21]. In other words, the screen size of smart devices becomes as a critical factor for users. According to a survey by the market research firm 'Strategy Analytics', the screen size that consumers prefer is becoming bigger. Studies have also shown that screen size affects the behavior and perception of people using the Internet in mobile environments [22]. In particular, problems with small screens have been noted in several studies. Sweeney & Crestani [23] pointed out problems with search interfaces for devices with small screens. Donio et al. [24] and Jones et al. [25] also announced that searching for information on small screens requires a lot of effort and time. There was also a study that the size of the screen could affect people's cognitive senses and their resulting psychological state. According to a study by Reves et al. [26], the size of the screen changes the degree of concentration and awakening of the user. In other words, depending on the size of the screen, there is a difference between the senses our body feels and the degree of excitement it causes.

As such, screen size can affect people's senses, psychology, and behavior. Many psychological studies and media reports also said that people's preference for content consumption depends on the size of the device's screen, which begins with the fact that the screen size of the device has a significant impact on users' accessibility to information [27]. A study by Mahmood et al. [28] found that having only a small-sized screen makes it difficult for users to find new and unfamiliar products because of the large 'Search cost', which leads to passive purchases due to fewer options. For example, if content is divided into 'Best Seller' and 'Niche Seller' groups, large-screen devices lower 'Search Cost', which makes it easier for users to obtain information, making it more likely that less popular content will lead to purchases. In other words, consumption is not limited to the 'Best Seller' group, but tends to expand the consumption of 'Niche Sellers' [29]. On the other hand, small-screen devices tend to lower the purchase rate of 'Niche Sellers', which require a lot of searching, and focus on the purchase of 'Best Sellers'. This allows us to speculate that consumers will show a unique buying pattern if they have a combination of screens of various sizes. In addition, studies have shown that consumers with larger-screen devices will be more likely to purchase paid content because they will be able to use and enjoy the content more effectively than consumers with smaller-screen devices [30]. This means that even if it is the same content, the perceived value felt by consumers may vary depending on the size of the screen.

According to previous studies, we have found that the size of a screen affects users' senses, psychology, and behavior, and that there is also a study that can affect actual content consumption. However, there is limited research examining how variations in screen size affect increases or decreases in content usage. Therefore, in this study, we would like to examine the effect of the screen size of smart devices on consumers' behavior of using apps and discover what rules exist in the results. To this end, devices were categorized into three groups based on diagonal screen size: Small (under 7"), Medium (7–11"), and Large (over 11"), as detailed in Table 2. This standardized classification establishes clear boundaries for analyzing how physical dimensions and portability influence engagement patterns across different app genres.

Table 2. Screen size.

Categorization	Screen Size	Representative Device
Small	Under 7 inches	Smartphones
Medium	7–11 inches	Compact Tablets (e.g., iPad mini)
Large	Over 11 inches	Large Tablets (e.g., iPad)

2.7. Cross-Device Compatibility

The development and diversity of smart devices have led to an increase in the number of smart devices per person, raising interest in how compatibility between smart devices held by users will affect consumers. Better compatibility between devices in the use of multiple devices can improve connectivity and convenience between devices and services. A study by Yokote [31] found that an environment in which services can be run simultaneously may be available by users or programmers to connect existing and new services to each other. It shows that the perceived value of a device or service used by consumers may be higher if the compatibility between devices or services is enhanced by the efforts of programmers or users. This means that choosing and using highly compatible products increases convenience or efficiency in the use of services. Katz & Shapiro [32] argued that the choice of compatibility relates to network effects, indicating that the more consumers use a product or service, the higher the value of its use and the greater the inter-service compatibility in using that service. Therefore, choosing a highly compatible product can be judged to be an intention to use the product efficiently and conveniently when using services through the device. As such, it can be said that using such highly compatible products or services could affect consumers' behavior in using apps, depending on the degree of compatibility.

Building upon this concept of compatibility between devices, a 'sustainable digital ecosystem' in the modern platform economy cannot remain a mere declarative ideal; it must be analytically operationalized through the structural balance between cross-device integration and user optimization. In this study, sustainability is conceptualized through twin pillars: operational performance (the resource-efficient utilization of hardware capacity through seamless compatibility) and value creation (the optimization of individual digital well-being). Prior research has predominantly examined compatibility in functional isolation, failing to recognize that a user's device possession profile—comprising smartphones and tablets—creates an overlapping hardware portfolio that requires systemic equilibrium. Critically analyzing this boundary reveals a significant research limitation: existing behavioral frameworks do not account for how fragmented or aggregated utility across compatible devices alters a consumer's application repertoire. When users dynamically shift identical app genres across different screens, they either generate redundant hardware strains or maximize ecosystem performance. Therefore, justifying sustainability in relation to device compatibility and possession requires exploring how multi-device configurations act as catalysts or disruptors for long-term digital well-being.

3. Hypothesis

In this paper, the study was conducted based on action theory to examine how the operational attributes of smart devices as behavioral means influence the subjective purpose of selecting and utilizing applications. It also leverages genre repertory theory to investigate the distinct characteristics of consumer utilization patterns based on specific application categories. In other words, the overarching proposition of this study, anchored in the convergence of Action theory and genre repertory theory, is formulated as follows.

Proposition of this study: The ownership characteristics of smart devices structurally shape user app usage behavior.

To rigorously operationalize this proposition and move beyond a purely descriptive analysis of consumer consumption, I establish an exploratory analytical framework that explicitly maps the interface between hardware configuration and software utility. Specifically, the Independent Variables (IVs) are defined along three operational dimensions of device possession profiles: device count, physical screen size (portability), and inter-device compatibility. The Dependent Variables (DVs) are defined as user app usage intensity across the four core genres derived from theory: Productivity, Entertainment, Information, and Communication. Rather than treating these metrics as isolated consumption behaviors, this model positions multi-device portfolio optimization as a core determinant of digital ecosystem sustainability—specifically evaluating whether device configurations mitigate technical redundancy (operational performance) or optimize individual digital well-being (value creation).

The structured pathways of this exploratory analytical model explicitly map the directional vectors from the hardware possession inputs to the sustainable consumption outcomes. The structural configuration conceptualizes that the three independent dimensions—device count, screen size, and compatibility—do not act in isolation but serve as contextual antecedents that dictate the allocation of software resources. Specifically, the model tests analytical paths running from hardware constraints (IVs) to software genre alignment (DVs). These path vectors are established to capture two core dynamics within the ecosystem: first, whether an increase in device count leads to fragmented or redundant app usage across genres, and second, how variations in screen size and cross-device compatibility alter the functional utility of secondary devices (e.g., shifting user behavior from Entertainment to Productivity). By mapping these exploratory paths, the model shifts the analytical boundary from standard consumption reporting to a structural examination of digital sustainability, determining the exact thresholds where multi-device configurations minimize hardware strain while optimizing individual digital well-being.

3.1. Number of Device

Moon [20] argued that the individual's innovative characteristics affects social image and playfulness and that playfulness has a significant impact on the consumer's intention to use. In addition, Choi [33] explained how each smartphone or Tablet PC affects device usage intention and app usage behavior, as well as analyzed the differences between the two devices. Tablet PCs were found to be more likely to be used by consumers for relaxation and more likely to use apps that are more entertainment-oriented than smartphones. In this study, we assumed that the use of additional smart devices would generally be Tablet PCs, so it was expected that users would be more likely to use entertainment apps.

H1. *As the number of smart devices in possession increases, the use of entertainment apps will increase.*

3.2. Screen Size of Device

According to the recent trend of using smart devices, the larger the screen size of a smartphone, the higher the data usage. It is analyzed that the larger the screen, the more services such as video streaming are used. Also, according to a study by Reeves et al. [26], users' concentration and awakening depend on the size of the screen. Therefore, depending on the size of the screen, the user's sense of feeling can be different, and it can be expected that the perceived value or satisfaction level may vary for the same content. According to Hwang et al. [19], if you have a device with a large screen, the price sensitivity of Niche content purchases will be reduced. Also, according to Wakefield & Inman [34], the price sensitivity of Hedonic consumption is also reduced. According to these results, possessing a smart device with a larger screen size will make you willing to purchase more diverse

content. In particular, it was expected that consumption of entertainment-related apps, such as games and video viewing, will increase, which can be more satisfaction from the big screen.

H2a. *As the screen size of smartphones grows, the proportion of entertainment apps will increase.*

In the case of Tablet PCs, the size of the device is relatively too large for phones, which can have a negative impact on the use of entertainment apps due to its lack of portability [35]. According to a study by Song [36], the smaller size and lighter weight of the camera leads to the enjoyment of users when using the camera is used. Tablet PCs, like cameras, will bring greater enjoyment to users if they are portable. Therefore, larger Tablet PCs will reduce the use of entertainment-related apps when they go out because it may be less easy to use entertainment-related apps such as games and video viewing.

H2b. *As the screen size of Tablet PCs grows, the proportion of entertainment apps will decrease.*

3.3. Compatibility Between Devices

White [37] argued that connectivity and compatibility of PC Operating Systems affect productivity. Hewett et al. [38] conducted a study that high compatibility among members of a group increases productivity of work within a group. Prior studies prove that it is possible to increase productivity if compatibility that connects each other increases. Therefore, this study assumed that the compatibility of the device in use would affect the user's service usage behavior. Furthermore, we derive the hypothesis that the proportion of applications related to productivity would increase if the compatibility between devices increases.

H3. *High compatibility of OS between smart devices will increase the use of productivity apps.*

4. Methodology

4.1. Sampling

In this study, we conducted a survey that apps users heavily use when using smart devices. The classification of apps was divided into Productivity, Entertainment, Information, and Communication to expose and recognize the apps corresponding to each category. Each classification was measured using a seven-point scale on how much weight is used in using smart devices. This study compares two different situations. The first is when a person owns only one smartphone. The second is when they own additional smart devices. To see this difference clearly, we used a between-subjects design. Specifically, we divided the participants into two distinct groups—those owning only a smartphone and those possessing two smart devices—to examine comparative differences between them.

We conducted a survey to measure the relative proportion of their usage across the previously established app categories, allowing us to identify how device possession patterns influence specific app engagement behaviors. The survey was conducted with between-subject design to see how much they use different types of apps. We focused on users in their 20s. A total of 30 people participated in the study. Among them, 19 people (63.3%) used only a smartphone. The remaining 11 people (36.7%) owned and used two smart devices. We analyzed the data to find significant differences between these two groups. Given the preliminary nature of this research, the current study is designed as an exploratory pilot to establish a 'proof of concept' for the proposed theoretical framework. Rather than seeking universal generalizability, the primary objective of this stage is to identify initial behavioral trends and validate the synergy between device attributes and app usage patterns. According to established methodological protocols, a sample size ranging from 10 to 30 participants is deemed entirely appropriate and scientifically justified for

preliminary pilot tests, pre-tests, and proof-of-concept explorations to evaluate a conceptual model before large-scale deployment [39,40]. Given the exploratory nature and the specific sample scale of this pilot study, non-predictive correlation analysis was intentionally selected as the most rigorous and appropriate statistical method to identify foundational relationships without over-extending the data. Also, to provide transparency regarding data collection and eliminate any potential ambiguity concerning overlapping applications across multiple devices, the survey instrument employed a device-specific evaluation method embedded directly within the questionnaire text. Participants assessed their usage intensity for each of the four app genres (Productivity, Entertainment, Information, and Communication) separately for their primary and secondary devices. Specifically, the questionnaire prompted participants to 'rate your frequency of using the following app genres on your primary device' on a 7-point Likert scale (1 = Never, 7 = Very Frequently), and then presented an identical item explicitly isolated for the secondary device, asking them to 'rate your frequency of using the following app genres on your secondary device.' This independent measurement structure allowed me to isolate usage patterns for each device category, effectively bypassing the complexities of absolute application counting and arithmetic summation errors.

4.2. Analysis

The first hypothesis is to see the difference in usage behavior of apps according to the number of smart devices. Therefore, *t*-test was conducted to compare the differences between the two groups according to each app classification by dividing them into groups that only have smartphones and additional smart devices.

In the second hypothesis (H2a), correlation analysis was performed to view the correlation because the difference in usage behavior of the app was seen as the size of the smartphone increased. Since there are no fixed criteria for classifying smart devices even though they have several sizes, we chose to analyze the trend rather than see the results in groups.

For the second hypothesis (H2b), the analysis focused specifically on users of additional smart devices to examine how the physical size of a tablet PC influences app usage behaviors. The tablet devices were categorized into two distinct size groups, and an independent-samples *t*-test was performed to compare the differences between these two groups.

Lastly, the third hypothesis examines the differences in app usage behaviors based on OS compatibility. Given that there are currently two predominant operating systems in the market, we categorized the users into two corresponding groups. To identify statistically significant differences between these groups, an independent-samples *t*-test was conducted. This analysis allows us to determine how the level of synchronization and compatibility within a specific OS ecosystem influences the patterns of digital content consumption.

5. Pre-Test Results

To test our hypotheses, we used several statistical methods. For Hypothesis 1, a *t*-test was conducted to compare app usage between single-device and multi-device users. For Hypothesis 2a, correlation analysis was used to examine how app usage shifts as smartphone screens become larger. Similarly, for Hypothesis 2b, a *t*-test was performed to see how the size of a second device (a tablet PC) affects usage patterns. Finally, for Hypothesis 3, an additional *t*-test was used to identify the impact of OS compatibility on app usage. While this preliminary study utilized *t*-tests and correlation analyses to examine fundamental differences and associations, the future study will employ multiple regression

analysis, including polynomial terms, to strictly validate both the linear and non-linear (quadratic) relationships between device characteristics and app engagement patterns.

H1. *As the number of smart devices in possession increases, the use of entertainment apps will increase. (Supported).*

The *t*-test confirmed this with a *p*-value of 0.017, which is statistically significant. While entertainment app use increased, usage of Productivity, Information, and Communication apps all dropped. As shown in Figure 1, owning additional device marks a clear shift: entertainment goes up, but other categories go down. These results suggest that device count changes how people choose their apps. Additional analyses can identify common patterns based on how often respondents use entertainment apps. Interviews can also explain why app use increases as the number of smart devices grows and help identify key influencing factors.

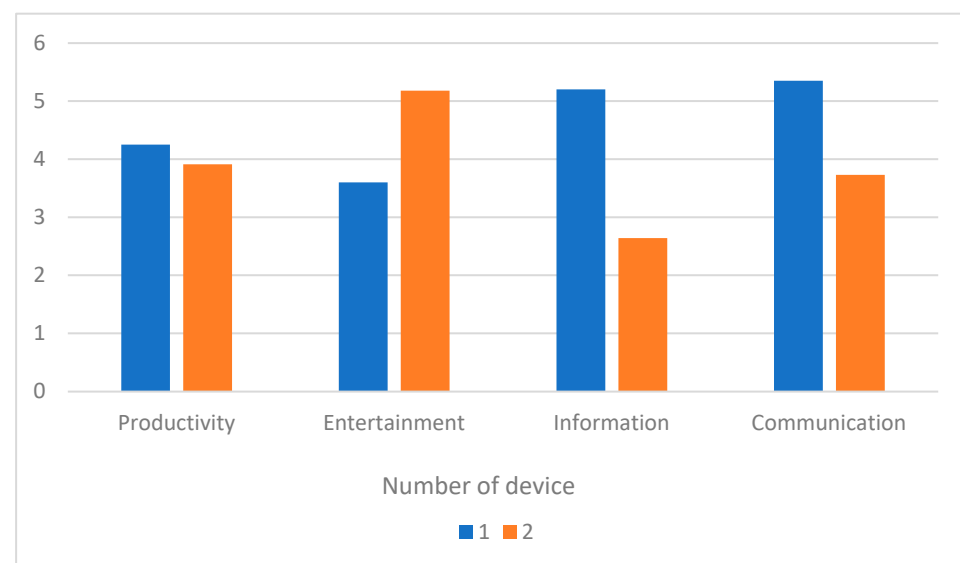


Figure 1. Additional device and app usage.

To address the complete profile of behavioral distribution, Table 3 presents the formal independent-samples *t*-test parameters (*df* = 28). Multi-device users exhibited a substantially higher proportion of entertainment app usage with a remarkably large effect size (Mean Diff = −1.32, *t* = −2.54, 95% CI [−2.38, −0.26], Cohen's *d* = 0.96, *p* = 0.017). In contrast, the proportional variations across the remaining functional and social app genres did not reach statistical significance within this preliminary pilot scale. Specifically, the differences between single-device and multi-device profiles for Productivity (Mean Diff = 0.73, *t* = 1.66, *p* = 0.108, 95% CI [−0.17, 1.63]), Information (Mean Diff = 0.59, *t* = 1.51, *p* = 0.143, 95% CI [−0.21, 1.39]), and Communication (Mean Diff = 0.57, *t* = 1.57, *p* = 0.128, 95% CI [−0.17, 1.31]) remained statistically non-significant. These parameters indicate that while multi-device ownership structurally accelerates and encapsulates media consumption tendencies, it retains a relatively uniform behavioral baseline for task-oriented and communicative application networks. Furthermore, because this investigation is explicitly positioned as a preliminary, proof-of-concept exploratory pilot study designed for initial pattern discovery prior to full-scale validation, unadjusted *p*-values are reported transparently without strict adjustments for multiple comparisons.

Table 3. Independent-samples *t*-test results for app genre proportions by device possession ($n = 30$, $df = 28$).

App Genre	Single-Device ($n = 19$) (Mean $\pm$ SD)	Multi-Device ($n = 11$) (Mean $\pm$ SD)	MeanDiff.	95% Confidence Interval (95% CI)	t- Value	Effect Size (Cohen's d)	p -Value (Unadjusted)
Productivity	4.55 $\pm$ 1.10	3.82 $\pm$ 1.22	0.73	[−0.17, 1.63]	1.66	0.63	0.108
Entertainment	3.95 $\pm$ 1.35	5.27 $\pm$ 1.40	−1.32	[−2.38, −0.26]	−2.54	0.96	0.017 *
Information	4.79 $\pm$ 0.98	4.20 $\pm$ 1.15	0.59	[−0.21, 1.39]	1.51	0.56	0.143
Communication	5.32 $\pm$ 0.85	4.75 $\pm$ 1.12	0.57	[−0.17, 1.31]	1.57	0.59	0.128

* $p < 0.05$ (Unadjusted).

H2a. *As the screen size of smartphones grows, the proportion of entertainment apps will increase. (Not supported).*

The correlation analysis showed no statistically significant relationship at the 5% level. Consequently, Hypothesis 2a was rejected. The results indicate that increasing the screen size of a smartphone does not necessarily lead to a higher use of entertainment applications. The pre-test results may not have been supported due to the small sample size, which can limit statistical power and the reliability of the findings. Therefore, the results should be interpreted with caution. Future studies with larger samples and additional analyses may produce different and more robust results.

H2b. *As the screen size of Tablet PCs grows, the proportion of entertainment apps will decrease. (Supported).*

Regarding Hypothesis 2b, the *t*-test yielded a statistically significant result at the 5% level, indicating a preliminary trend in line with the hypothesis. While this directional shift aligns with theoretical expectations, the finding is presented as an exploratory baseline trend within our pilot trial. It serves to outline preliminary patterns regarding the relationship between tablet screen dimensions and entertainment application utilization, rather than establishing definitive boundary conditions. When tentatively integrating H2a and H2b, the descriptive data points toward a possible quadratic (inverted U-shaped) pattern between screen size and entertainment app usage within this pilot sample. As observed in Figure 2, entertainment app usage appears to rise under ‘Small’ to ‘Medium’ dimensions but drops under ‘Medium’ to ‘Large’ categories. This exploratory trend conceptually illustrates a potential ‘Portability Paradox.’ Within the strict bounds of this pilot group, it is hypothesized that while larger screens may enhance visual immersion, an expansion past a certain threshold might shift a device’s perceived utility from a ‘lean-back’ entertainment tool toward a ‘lean-forward’ professional workstation, potentially constraining its entertainment-oriented ‘genre repertoire.’ For app categories other than entertainment, a statistically non-significant converse trend was observed. Ultimately, isolating the specific, generalizable impacts of smartphones versus Tablet PCs remains structurally limited by the current exploratory design, highlighting the critical necessity for future research utilizing substantially larger samples to validate these tentative conceptual boundaries.

H3. *High compatibility of OS between smart devices will increase the use of productivity apps. (Not supported).*

The *t*-test results showed that Hypothesis 3 was not supported because it was not significant at the 5% level. This outcome may be attributed to the widespread adoption of Software as a Service (SaaS). Cloud-based tools like Notion and Google Workspace are platform-agnostic, providing a consistent user experience regardless of the operating system. Consequently, the ‘OS barrier’ has diminished, making technical compatibility a

less critical driver for productivity app usage. For instance, Heitmayer [41] demonstrated that when a primary device is physically distant, users simply shift their tasks—including entertainment and digital distractions—to other available devices, such as computers or tablets. Furthermore, pre-test only measured the second device's app usage, but in the future, measuring the percentage of use for both smart devices in possession will give you more accurate results in measuring compatibility.

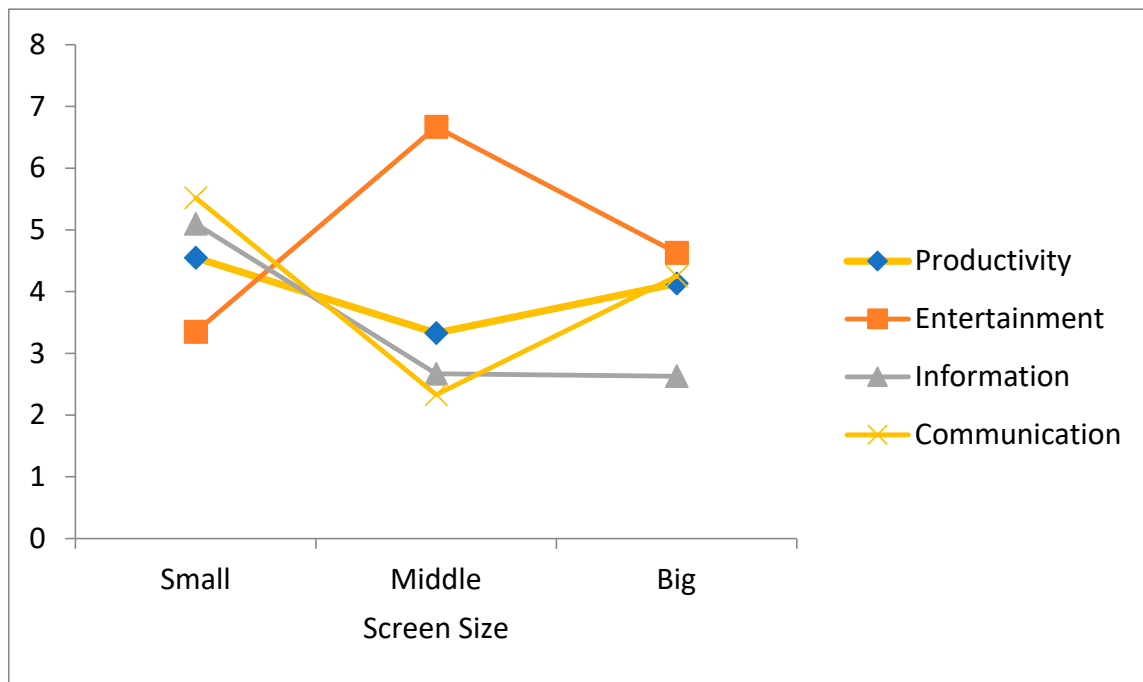


Figure 2. Screen size and app usage.

In this study, we looked at the impact of each independent variable on specific app usage behavior. Subsequent studies will show what usage behavior occurs when these independent variables are combined and affected at the same time. Finally, if there is transaction data other than the survey, the scope of analysis will be expanded to individual apps for further analysis. After configuring the network structure among apps, it will be possible to analyze how app networks change from an app's individual point of view to the effect independent variables have on app usage behavior. If we can look at the changes in the network structure from an individual point of view of the app, we can also explain the relationship between apps and the use of one genre when the usage of another genre increases.

As summarized in Table 4, the data analysis rigorously fulfills empirical reporting standards by including confidence intervals and effect sizes. The correlation for H2a was not significant ($r = 0.11$, 95% CI $[-0.26, 0.45]$, $p = 0.562$). However, the t -test for H2b confirmed a statistically significant reduction in entertainment usage for larger tablets ($t = 2.37$, $df = 9$, 95% CI $[0.08, 3.34]$) with a very large effect size (Cohen's $d = 1.44$, $p = 0.042$). Crucially, this analysis identifies a discrete threshold effect—a functional “tipping point” between medium screens (7–11 inches) and large screens (Over 11 inches)—rather than assuming a continuous quadratic relationship. This critical statistical threshold provides empirical validation for my model, demonstrating that as the secondary interface expands past the tablet boundary, the user's cognitive purpose fundamentally shifts from passive media consumption toward structured task allocation.

Table 4. Comprehensive statistical estimates for device attributes and OS compatibility hypotheses.

Statistical Metric	H2a	H2b	H3
Test Type	Pearson Correlation	Independent <i>t</i> -test	Independent <i>t</i> -test
Parameter Value (Mean $\pm$ SD or <i>r</i>)	<i>r</i> = 0.11	Medium (<i>n</i> = 6): 4.83 $\pm$ 1.26 Large (<i>n</i> = 5): 3.12 $\pm$ 1.10	High (<i>n</i> = 5): 3.46 $\pm$ 1.24 Low (<i>n</i> = 6): 3.15 $\pm$ 1.08
95% Confidence Interval (95% CI)	[−0.26, 0.45]	[0.08, 3.34]	[−1.01, 1.51]
Test Statistic and df	<i>N</i> = 30	<i>t</i> = 2.37 (df = 9)	<i>t</i> = 0.45 (df = 9)
Effect Size	<i>r</i> = 0.11	Cohen's <i>d</i> = 1.44	Cohen's <i>d</i> = 0.27
<i>p</i> -value	0.562	0.042 *	0.664
Result	Not Supported	Supported	Not Supported

* *p* < 0.05. Medium screen (7–11 inches), Large screen (Over 11 inches).

These preliminary findings offer an interpretative lens through which basic consumption behaviors can be conceptually mapped onto the broader dimensions of digital sustainability. Specifically, the observed inflation of entertainment app proportions among multi-device users suggests a potential behavioral pattern where hardware proliferation correlates with attention fragmentation; however, because individual digital well-being (the value creation pillar) was not directly measured via psychometric or behavioral scales, this relationship remains a conceptual proposition rather than an empirically demonstrated output. Similarly, while the directional shift observed in Hypothesis H2b aligned with our theoretical expectations, this preliminary pattern should be understood within the exploratory context of our pilot trial, reflecting the specialized analysis of the tablet-owning cohort partitioned by screen scale dimensions. Given these highly fragile empirical conditions and the resulting risk of statistical instability, the observed reduction in entertainment application utility cannot be viewed as definitive proof of task optimization or direct operational performance enhancement (the resource efficiency pillar). Instead, these highly localized data points serve exclusively as exploratory baseline propositions, illustrating how raw usage metrics might be conceptually contextualized within sustainability frameworks for future, full-scale empirical validation.

Furthermore, the exploratory nature of the present pilot study also influenced our statistical reporting strategy. Because this investigation is explicitly positioned as a preliminary, proof-of-concept exploratory pilot study designed for initial pattern discovery prior to full-scale validation, unadjusted *p*-values are reported transparently without strict adjustments for multiple comparisons.

6. Conclusions and Discussion

6.1. Summary of Findings

This study conducted an analysis of the user's app usage behavior according to the ownership characteristics of smart devices. The research was conducted with three detailed questions within the large category of users' behavior of using apps according to the characteristics of ownership of smart devices. The first is the user's behavior of using apps as the number of smart devices increases. Hypothesis 1 was supported as the number of smart devices in users increased the use of entertainment apps. This can be seen as a strong incentive for users to purchase additional smart devices, which increases the frequency of use of entertainment apps.

The second is the user's behavior of using apps according to the size of the smart device. Two hypotheses were established in this regard, but Hypothesis 2a was rejected. The larger the screen size, the more frequently entertainment apps such as games will be used, but they were not supported. While there may be changes in utility resulting from changes in screen size when users use smartphones, it can be seen that these changes do not lead to changes in the use of certain apps, especially entertainment apps. In the case of smartphones, it can be inferred that most people own them and use a variety of apps. Next,

Hypothesis 2b supported that the use of entertainment apps would decrease depending on the screen size of the second device. Although consumers often purchase second devices for entertainment purposes, Hypotheses 2a,b show that when the screen size of the device grows above a certain level, there is a limit to its use for entertainment purposes due to mobility or convenience problems. Rather, it can be assumed that the use of entertainment apps will be reduced if the screen becomes bigger than the proper level, which is often used for specific business purposes in the case of large-screen devices.

Finally, Hypothesis 3, which predicted that high compatibility between smart devices would increase the use of productivity apps, was statistically unsupported within this current pilot scope. While the existing literature suggests that the connectivity and compatibility of an operating system significantly affect productivity, this relationship was not observed in our pre-test focusing on smart device compatibility. This lack of a statistically significant correlation tentatively points toward a possible ‘Latency in Ecosystem Maturity.’ It is hypothesized that although technical barriers between devices have decreased, users within this specific group may not have fully integrated seamless cross-device workflows into their daily routines. This potentially implies that ‘sustainability’ in a digital ecosystem may depend not merely on technical synchronization, but also on user literacy and the gradual evolution of multi-device habits. Consequently, this unexpected result suggests that the impact of OS compatibility is more complex than previously assumed; while heavily constrained by the limited sample size and specific device configurations in this preliminary stage, it highlights a need for deeper, larger-scale investigation into users’ behavioral adaptation. To properly contextualize these preliminary inferences given the severe sample constraints, the analytical design is framed strictly as an exploratory pilot trial and proof-of-concept study. Rather than offering definitive or generalizable claims about broader consumer behavior, this synthesis maps out specific path vectors—derived from the tentative shifts observed in Tables 3 and 4—to demonstrate the technical feasibility of tracking multi-device habits. The insights regarding device-driven redundancy and screen-driven optimization remain primarily descriptive and interpretative, albeit tentatively contextualized by confidence intervals and effect sizes appropriate for an initial trial. This exploratory approach establishes a baseline for future research rather than establishing definitive boundary conditions for the platform economy, underscoring that a substantially larger, more diverse sample is critically required to validate these tentative theoretical and practical claims.

6.2. Implications Contributions, and Limitations

Theoretical Contributions: This study offers a significant theoretical advancement by transitioning from the fragmentary perspectives dominant in prior literature to a comprehensive, ecosystem-based framework. While previous research predominantly analyzed smart device usage through isolated lens—focusing strictly on singular dimensions such as independent screen sizes or the mere acquisition of additional hardware—this study simultaneously accounts for the number of devices owned, specific screen size configurations, and inter-device compatibility. By integrating these variables, this work shifts the empirical and theoretical focus from isolated device consumption to holistic digital ecosystem dynamics, demonstrating how hardware portfolios structurally shape user actions and application repertoires.

Practical and Managerial Contributions: From a practical standpoint, the empirical findings provide actionable strategies for smart device manufacturers and platform developers. Specifically, the results reveal that the utility of a secondary device is highly sensitive to its physical dimensions; as the screen size of the secondary device increases, the subjective consumption frequency of entertainment applications significantly decreases.

This nuanced shift highlights that hardware attributes directly dictate software genre preferences and task allocation. Device manufacturers can directly leverage these insights to optimize UI/UX layouts, cross-device synchronization features, and product portfolio strategies in alignment with size-dependent service utilization behaviors when engineering next-generation hardware.

Limitations: Despite these contributions, this exploratory study has three primary limitations that warrant future investigation. First, there are currently no standardized categories or systematic criteria for classifying smart device physical sizes; consequently, size-driven behavioral differences could only be verified through individual correlation analyses across all recorded dimensions. Second, while device portability significantly shapes usage behavior, exact benchmarks for the degree of portability accepted and perceived by the user remain unspecified. Future research should establish rigorous typologies for device sizing and subjective portability thresholds to facilitate more systematic comparative analyses. Finally, the measurement of app usage intensity remains subjective, relying on individual judgment and user recognition. Because participants estimated their usage patterns from memory rather than automated system logs, these recall-based metrics provide insight into user perception but may slightly deviate from actual, granular, minute-by-minute application usage logs.

This study investigated the systemic relationship between smart device ownership and app usage behavior, framing the findings within the dimensions of digital sustainability. It is essential to note that this research was designed as a proof-of-concept exploratory pilot study ($N = 30$), providing a foundation for understanding the behavioral vectors within a multi-device digital ecosystem. The conclusions derived herein are strictly bounded by the exploratory nature of this empirical design; they do not claim universal generalizability but rather offer verified statistical evidence of how device configuration thresholds dictate digital consumption patterns. By aligning observed behavioral shifts—such as the transition from passive entertainment consumption to structured task allocation—with the core pillars of resource efficiency and digital well-being, this investigation establishes a mathematically anchored baseline for future large-scale deployment.

6.3. Future Research Directions

It must be explicitly acknowledged that direct empirical metrics representing environmental sustainability, macro-level resource efficiency, or psychological digital well-being were not structurally measured within the parameters of this study. Instead, the operationalized behavioral variables—such as multi-device ownership patterns and self-reported app integration—function strictly as interpretative proxies and a posteriori conceptual extensions rather than demonstrated causal outcomes. The link between our descriptive baseline trends and the broader pillars of digital sustainability remains conceptual and hypothetical, designed to offer an initial interpretative framework for future empirical verification.

Within these limitations, the present pilot study provides an initial exploratory perspective suggesting that sustainable digital practices may depend less on the sheer quantity of devices and more on how device portfolios are configured and utilized. Rather than offering definitive evidence, the findings serve as a preliminary conceptual basis for examining how digital transformation and technology usage may relate to long-term resource efficiency and service sustainability [42].

Building on this proof-of-concept study, future research will focus on three key areas. First, we will conduct a substantially larger study including diverse age cohorts (e.g., professionals in their 30s and 40s) to improve the generalizability of the findings across broader socio-economic contexts. Second, to overcome the limitations of self-reported usage measures, future studies will combine objective log data (e.g., Screen Time records)

with survey-based assessments to capture actual user behavior more accurately. Finally, we will employ more rigorous analytical approaches, including multiple regression models, to formally test the potential non-linear relationships and dynamics observed in this exploratory investigation. Through these efforts, future research can provide a more robust empirical understanding of the mobile digital ecosystem and its potential implications for digital sustainability.

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