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Determining how application type moderates Gen Z consumers' intentions to switch to paid mobile services: A study of the Push-Pull-Mooring Framework

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Abstract

This study investigates factors influencing Z generation consumers' willingness to pay when switching from free to paid applications (apps). These factors include personal characteristics, product characteristics and availability, and perceived performances of the service providers. The study employs an exploratory approach to assess a structural model that organizes these variables within the framework of a push-pull-mooring (PPM) framework. In this empirical study, the SmartPLS was used for the purpose of model testing and moderator analysis. The survey results, which included 239 respondents, identified *price value of premium apps, dissatisfaction with free apps, perceived performance risk of free apps, price-quality inference, positive reputation of apps,* and *free mentality* as the factors most influencing consumers' switching intention. A comparison of hedonic (pleasure-oriented) and utilitarian (productivity-oriented) apps showed significant differences in switching intentions, influenced by security and privacy related concerns. The study identified two factors that were found to differ between groups in terms of their impact on the intention to transition to paid apps: *perceived security risks associated with free apps and consumers' privacy concerns*. The study's original contribution lies in its formulation of a comparative model and subsequent findings, which address salient aspects that mobile apps developers should consider when formulating their pricing strategies.

Keywords Freemium, Premium, Mobile applications, Switching intention, Moderation, Hedonic, Utilitarian, Multi-group analysis, PLS-SEM

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1. Introduction

According to the latest estimates from the GSMA (2025), mobile technologies and services currently contribute approximately 5.8% to global GDP, with a similar contribution of around 5% to GDP across Europe. This represents a substantial economic value of $6.5 trillion and almost €1.1 trillion in added value. It is projected that by 2030, there will be unique mobile subscribers in Europe, reaching an 89% penetration rate.

Entertainment apps were the top-grossing mobile app categories during the first quarter of 2024 (Statista, 2025a). According to a report on the most popular app categories worldwide, tool apps such as VPNs, browsers, and video players, were the most downloaded category in 2024. Communication apps were the second most popular. Productivity apps ranked third (Statista, 2025b). The app market is home to a wide variety of services, including games, business, education, lifestyle, utilities, entertainment, and more. The monetization strategies of mobile apps, however, show that 98% of worldwide revenue comes from free apps (Buildfire, 2024). Pricing strategies varies in digital world of services as free and paid apps.

Krämer & Kalka (2016) classification of digital pricing strategies encompasses four distinct categories. The first category, designated as "for free," involves the provision of B2C services free of charge, with advertising serving as the primary revenue stream. The second category, "freemium," entails the provision of a basic service or a limited period of use free of charge, with upgraded services incurring a cost. Examples include LinkedIn and Spotify. The third category, "subscription models" or "premium," prohibits the provision of any free product or service. The fourth category, "flexible pricing/dynamic pricing," pertains to pricing strategies employed by online retailers and online travel booking platforms (Öztürk, 2025). The utilization of both free and premium options is a prevalent practice across numerous sectors, including but not limited to education, data storage, data security, gaming, newspapers, media streaming, and social networks (Brüggemann & Lehmann-Zschunke, 2023).

People are more interested in something when they see that it costs nothing. The "zero-price effect" phenomenon (Niemand et al., 2015) represents the dual role of price, where a free offer minimizes the perceived sacrifices of consumers and creates the perception of receiving greater benefits or quality from a product. First, it signals more value because it does not include any monetary costs. Furthermore, consumers judge prices, and form an attitude or willingness to pay based on their reference prices. Since free offers tend to be lower than consumers' reference prices, which range from free to premium prices for a specific service, free services or freemium are effective in increasing willingness to pay (Wagner et al., 2014). Additionally, zero-price products likely stir more enjoyment, thereby inverting the price-quality relationship, and increasing consumers' perception of value (Niemand et al., 2015). Brüggemann & Lehmann-Zschunke (2023) used prospect theory and vendor lock-in theory to explain the termination decision of premium users when there is clear negative disconfirmation. The analysis of factors that influence the termination of freemium business models has the potential to provide freemium providers with the ability to predict cancellations, and respond in a timely manner. This is crucial for turning free uses into paid ones.

The purpose of this study is to explore the factors that can influence Gen Z consumers' switching intention, to paid apps and to understand how intention to pay for apps differs in terms of orientation (category) of mobile apps. Mobile app consumption is highest among young consumers. The average monthly hours spent on mobile apps by consumers aged 18-24 is 112, topping all other age groups (Buildfire, 2024). Forbes (2022) reports that around 40% of mobile users worldwide are from Generation Z. This generation is considered the "mobile-first generation" because they are young adults who use mobile devices to a greater extent than other age groups. Consequently, they are selected as a subject of research interest.

To this end, the study employs the PPM framework. The research process began with identifying the factors that determine the intention to pay in mobile services. In this process, the relevant variables in studies examining this topic were identified. These include the PPM model and other relevant consumer behavior models. The study determined the positive or negative role these variables play in the given contexts. Subsequently, these variables were classified based on their relative importance in the purchasing and payment intentions of young consumers, in line with the scope of the study. The research model was determined to investigate the relative relationships between variables that motivate purchasing (pull), variables that can inhibit purchasing (push), and other personal, social or contextual factors that can influence behavioral change (mooring variables).

Initially, the study's original value and theoretical framework must be discussed in terms of its field, scope, and selected variables. Studies investigating the factors affecting the intention to pay and/or switch, which are relevant to the purpose of this research, are limited. To date, no study has been found that explores differences among various types of mobile services through the lens of young consumers. It is anticipated that the most significant theoretical contribution of the study will be in this regard.

Secondly, the contributions made in terms of the PPM model will provide additional value for other researchers who will use this framework. The PPM model is a framework that has been applied in many areas to investigate changes in consumer behavior. The model has been chosen for the following reasons, as outlined in this research:

- The results of studies conducted on this model summarize the factors that determine a consumer's decision to abandon a product/service they have previously consumed or are currently consuming, and choose to use another product/service. The significance of this model lies in its ability to encompass a wide range of factors, including both the negative aspects of the abandoned product, and the positive aspects of the migrated product, as well as personal and social variables in a broader scope.
- The model's exploratory basis allows for updating of the consumer behavior model by adding and renewing sub-variables in line with research in the field. The PPM's adaptable and self-updating infrastructure allows for the creation of unique behavioral narratives by each researcher.

Therefore, adapting this model in the lite rature and developing it by modeling the behaviors of Turkish Generation Z consumers is one of the original theoretical contributions of this study. Third, understanding the concept of willingness to pay or switching behavior to premium/paid services is meaningful in the design and management of free and premium service strategies. Price setting for mobile services is a complex matter. For instance in freemium model, it is difficult to determine the optimal pricing strategy to encourage the conversion of free users into premium users. Initially, the free use of a product or service is an attractive incentive for potential users. Therefore, as Niemand et al. (2019) stated companies first focus on increasing the free user customer base. However, according to data on conversion rates, it often proves to be unsuccessful. Increasing conversion rates was also a research focus. For instance, Wagner et al. (2014) recommended that companies offering freemium services enhance the probability of user conversion by ensuring a stronger functional fit between their free and premium offerings. This concept is referred to as premium fit. In mobile games category, Ross (2018) revealed that usage time, defined as the duration of user engagement with an app, emerged as the most effective predictor of monetization outcomes, while referring positive correlation between customer loyalty and monetization of freemium platforms (Brüggemann & Lehmann-Zschunke, 2023). Mäntymäki et al. (2020) have demonstrated that intention to upgrade to premium is predicted by variables including enjoyment and price value, whereas for premium users, attribute-level perceptions such as discovery of new content, ubiquity, and social connectivity drive their continued use of the premium service. Runge et al. (2022) stated the importance of the fit between the base product and premium features to facilitate the process. Furthermore, as the base product becomes more utilized, there is an increased probability of incorporating additional premium features. This, in turn, can lead to higher-priced premium purchases, which can enhance the perceived value of the base product. Martins & Rodrigues (2024) analyzed consumers' motivations for adopting freemium services, and converting to premium versions. They identified ubiquity, perceived value, and satisfaction as key drivers.

As seen, understanding the motivations to transition to paid services remains an area of ongoing research interest.

Summarizing the originality and value of this study, the following research questions are defined:

- *Research Question 1:* How do Gen Z consumers' risk perceptions and dissatisfaction with free apps affect their intention to switch?
- *Research Question 2:* To what extent do the following relate to the intention to switch to premium apps: apps characteristics, perceived app reputation, perceived value of premium apps, and attitudes toward premium apps?
- *Research Question 3:* To what extent do the availability of free substitutes, consumers' free mentality, price-quality inferences, and privacy concerns relate to the intention to switch to premium apps?
- *Research Question 4:* Can the type (orientation) of apps moderate the relationship between all (push, pull, and mooring) factors and switching intention?

2. Theoretical Framework and Hypotheses Formulation

2.1. Theoretical basis of the PPM framework

The PPM was initially developed for the study of human migration. The "push-pull" framework (Bogue, 1969; 1977), expanded to include mooring variables, posits that individuals are motivated to migrate from their places of origin due to negative factors, while positive factors serve as draws to their destination (Moon, 1995); and push and pull factors interact with "mooring factors," personal and social factors that bind potential migrants to their origins or facilitate migration the new destination (Marx, 2025).

This model has been examined in accordance with its relevance in the context of service switching behavior by researchers after its introduction by Bansal (2005), and it has been found to be valuable in the services marketing context. According to Bansal (2005), the characteristics of human migration are similar to consumers switching service providers.

Since then, it has been used in many different services in online or mobile, including the investigation of migration among social networks (Chang et al., 2014), web browsers (Ye & Potter, 2011), cloud storage services (Mohd-Any et al., 2024), mobile instant messaging apps (Sun et al., 2017), mobile payment apps (Kuo, 2020; Wang et al., 2019), internet-only banks (Yoon & Lim, 2021). Others include travelers switching to sharing accommodation platforms, and AI beauty platforms (Nugroho & Wang, 2023), and research that payment intention related such as subscribing to video streaming platforms and over-the-top (OTT) services (Tsai, 2023; Wu et al., 2025), paying for social question-and-answer services (Liu et al., 2021), and so on.

All studies identify their own factors to explain how their research model fits into the PPM framework. The general structure encompasses a range of variables, including push factors such as satisfaction/dissatisfaction, regret, perceived sacrifices, low service and fatigue; pull factors like alternative attractiveness, relative advantage, relative benefit, usefulness, enjoyment and subjective norm; and mooring factors including inertia, habits, attitude towards switching, and switching costs.

2.2. Model conceptualization and hypothesis development

The study’s research model includes a variety of variables sourced from the PPM model, and other research on consumers’ intention to use and willingness to pay for premium mobile services. The push factors defined in the research model are perceived sacrifices related to free mobile service use and dissatisfaction with free versions. The pull factors are identified as the characteristics of apps, consumers’ perception of app reputation, the perceived value of premium apps, and attitudes toward premium apps, in relation to their potential role in influencing switching intention. Personal and contextual factors that relate positively or negatively to consumers’ switching intentions are titled mooring factors. These include the availability of free substitutes, consumers’ mentality toward free services, their price-quality inferences, and their privacy concerns. Here is an examination of these variables in terms of their conceptual and theoretical significance.

2.2.1. Perceived sacrifices of free apps (perceived risk)

The decision to install an application by a consumer is often influenced by their risk perceptions (Harris et al., 2016). For free users, Brüggemann & Lehmann-Zschunke (2023) declared that the expected risk is important for customers deciding whether to continue a premium subscription or subscribe to a premium version for the first time. When decisions regarding consumption are made, monetary risks are typically the first considerations. For instance, even when consumers are considering a subscription to a video streaming service with a free trial period, they tend to prioritize the cancellation policy (Wu et al., 2025). This is due to the potential financial risks associated with paid services. It should be noted that no payment is included for the free use period of the premium, and no monetary risk is involved, at least in the short term. Therefore, it is important to look also into the non-monetary risks for any decision about a trial or use. As stated in the marketing literature, there are several non-monetary risk considerations, including performance, psychological, social, and so on (Casidy & Wymer, 2016).

According to Forsythe & Shi (2003), there are six types of risk: financial, product performance, psychological, time loss, social, and physical. Financial risk is defined as a net loss of money to the consumer, and can manifest in several forms. Product performance risk is defined as the potential for the application to malfunction or underperform according to expectations. When selecting applications to install, consumers frequently lack the option to evaluate their full functionality prior to making a purchase decision (Harris et al., 2016). Social risk is the perceived chance of experiencing a social loss (e.g., social embarrassment). Psychological risk is the likelihood of suffering a psychological loss, such as a more negative self-image (Casidy & Wymer, 2016). In online context, psychological risk encompasses disappointment and the emotional distress of frustration that consumers encounter when their personal information is disclosed. As indicated by Kim et al. (2008), other research has identified this category of risk, comprising privacy and security risk related to information disclosure. The time and convenience risk is the loss of time and hassle when trying to select, purchase, download, and install an app. For example, there might be a problem with the customer's account when they try to make a purchase, or the app might crash after the purchase (Harris et al., 2016).

This study has identified "performance/quality risk", and under the category of pychological risk, "security/privacy risk" as variables, in accordance with research on different monetization strategies in the sector and consumers' intentions to use online/mobile services.

Performance or quality issues are inherent in services, particularly in the case of information-based services. Performance risk is tend to higher for poor products in value that are low-priced, and for services especially because of their intangible nature.

Mani & Chouk (2018) refered security risk as a person's concerns about the potential loss of control over personal and private information due to intrusion by potentially dangerous individuals or fraudulent behavior by organizations. In essence, security risk is synonymous with uncertainty and the possible unfavorable outcomes associated with technology-based services. The underlying effects are attributable to both system performance and the behaviors of the individuals involved in the process.

Thus, the following hypothesis is suggested.

> H1. (a) Perceived performance risk, and (b) perceived security risk of free apps have positive effect on the intention to switch to premium applications.

2.2.2. Dissatisfaction with free apps

Research indicates a positive correlation between consumer satisfaction and repurchase intention. Dissatisfaction occurs when a customer's expectations for a product are not met (Chang et al., 2014).

This relationship is illustrated as the correlation between dissatisfaction and the intention to switch providers within the PPM framework. As stated in the selected framework, Liu et al. (2021) identified dissatisfaction as a driving (push) factor, explaining why consumers are willing to switch to paid social Q&A services. Ashilah et al. (2025) also state in their study that user dissatisfaction exerts a positive and significant influence on the intention of users to switch to premium services in a mobile-assisted language learning application. The authors stated the results as being consistent with those reported by Kuo (2020), who indicated that low user satisfaction with system and information quality leads consumers to switch to other mobile payment services.

According to Marx (2025), dissatisfaction is a critical variable within the PPM research framework, and it has been demonstrated to increase switching intention, as predicted by the expectation-confirmation theory of consumer behavior models.

Also noted in a systematic literature review, dissatisfaction emerges as a common theme in many studies (Chi et al., 2021; Fan et al., 2021; Xu et al., 2014; Yoon & Lim, 2021), indicating that negative experiences and dissatisfaction with the existing offering can push customers towards considering different alternatives in services or platforms (Krishnan & Raghuram, 2024). Accordingly, the following hypothesis is proposed.

> H2. Dissatisfaction with free apps has a positive effect on the intention to switch to premium applications.

2.2.3. Application characteristics and perceived positive reputation

With its characteristics, mobile commerce offers users more flexibility and access to variety of online information and services. This makes the mobile context more attractive than others. Most consumers understand that mobile services on mobile devices are characterized by ubiquity, encompassing most of the advantages of m-commerce. Okazaki & Mendez (2013) listed the key values of mobile as "immediacy, mobility, and searchability". Immediacy is related to the responsiveness of mobile services, facilitating easy and rapid actions. Mobility refers to the absence of location constraints. Finally, searchability refers to the absence of limitations on time and place, while searching for a wide variety of data (Chang et al., 2017). Therefore, when it comes to picking a mobile service, it is key for service providers to go above and beyond what is expected. They should base their service qualifications on these characteristics.

The technology in virtual environments can make a user's experience better or worse. Information fit with the tasks or visual appeal relates to consumers' in increasing perception of value (Yang, 2024). A good reputation also depends on the characteristics of the app.

As part of their study on consumers' perceived value and subscription intention for video streaming platforms, Wu et al. (2025) stated that maintaining subscriber trust, data security, and content quality is essential to a service provider's reputation. Consumers prioritize platforms that offer high quality, dependable content. The authors also noted that offering a free trial before payment can potentially enhance a company's image and credibility. The platform reputation is associated with increased payment intentions and elevated satisfaction levels. It is also stated that perceived brand reputation is sourced from several factors, including high-quality content, robust data security capabilities, an array of privacy options, and enhanced transparency, all of which are designed to increase consumer trust.

According to the literature on migration, it is important to consider the role of image, reputation, and novelty in decision-making processes related to switching (Bansal, 2005). Thus, the following hypothesis is proposed.

> H3. (a) Application characteristics, and (b) perceived positive reputation have positive effect on the intention to switch to premium applications.

2.2.4. Perceived value of premium apps

Perceived value (Zeithaml, 1988) has been identified as a critical factor in determining the use and benefits perceived by consumers of a given product based on the costs (Wang et al., 2020), and in influencing their purchase decisions. Various types of value that impact the buying process have been identified in previous research, such as functional, social, emotional, cognitive, and conditional value (Aprianingsih et al., 2024). In their investigation of the intention to purchase digital items within social networking communities, Kim et al. (2011) regarded value as having three dimensions: functional, social, and emotional.

As defined by Sheth et al. (1991) and Sweeney & Soutar (2001), the most commonly referenced value dimensions are as follows: "Quality/Performance value" is the utility that is derived from the perceived quality and expected performance of the product. The perceived quality and performance can be thought of as similar to the concept of perceived usefulness. "Emotional value" is defined as the utility derived from the feelings or affective states generated by an item. According to Kim et al. (2011), the term "item" refers to an entity capable of eliciting certain feelings or emotional responses. "Social value" is defined as the utility derived from a product's potential to enhance social self-concept and social well-being (Kim et al., 2011). "Price value" (The value-for-money) is the utility gained from the product that results from the reduction of perceived short-term and longer-term costs (Hsu & Lin, 2015; Tyrväinen & Karjaluoto, 2024).

The existing literature has identified a strong correlation between perceived value and behavioral intentions related to digital services, including mobile shopping, mobile payment services (Lin et al., 2020), music streaming (Fernandes et al., 2019), gaming (Hsu & Chen, 2018), freemium services (Hamari et al., 2020), augmented reality (AR) mobile applications (Trivedi et al., 2022), etc.

Martins & Rodrigues (2024) proposed that perceived value influences platform adoption and premium conversion. In music streaming services, decisions to remain premium are based on other constructs, such as discovering new music or ubiquity, when presented with a sufficiently good price-value ratio. Hsu et al. (2024) stated that the fit between perceived value and user needs is crucial for influencing users' payment intentions and purchasing behaviors. In predicting the intention to pay, Hsu & Lin (2015) included app ratings, free alternatives, and habit in their expectation-confirmation model, which indicates that confirmation is positively related to perceived value and satisfaction. They found that value for money, app ratings, and free alternatives to paid apps directly affected the intention to purchase paid apps.

As indicated by Hamari et al. (2020), social value and enjoyment (emotional value) are positively correlated with increased purchases of premium products and services. The researchers determined that an increase in the perceived value of the freemium service (i.e., enjoyment) has the potential to positively or negatively impact future profitability, depending on whether it leads to increased customer retention or reduced monetization, respectively.

Cao et al. (2025) propose that perceived value is positively related to SaaS use continuance intentions. Wu et al. (2025) presented a model of the intrinsic and extrinsic motivational factors that influence free users' intention to pay for mobile TV services, which are entertainment-based apps. The authors identified value (functional, emotional, economic, and social) as a direct influence on habits and subscription intentions. Functional value was identified as important for streaming service functionality and efficiency. Emotional value is important because it depends on personalization, user experience, and nostalgic elements to influence subscription intentions. Previous research has shown that video streaming systems that evoke happiness, relaxation, and nostalgia tend to keep more users. All have economic value, but streaming platforms could significantly boost their social value by offering features that encourage community interaction and human connection, as well as exclusive content and virtual watch parties. According to Wu et al. (2025), three factors, service quality, perceived value, and social influences, were found to predict subscription. Thus, this study proposes the following hypotheses:

> H4. (a) Perceived quality value, (b) perceived price value, and (c) perceived emotional value have positive effect on the intention to switch to premium applications.

2.2.5. Attitude towards premium apps

Attitude refers to the degree to which an individual has a favorable or unfavorable evaluation of a planned behavior. The prevailing consensus among scholars in the field is that the defining characteristic of an attitude is its evaluative dimension, which can be categorized as positive or negative. In the theoretical framework of the theory of planned behavior, attitude is conceptualized as a pivotal factor influencing behavioral intention (Ajzen, 1991).

As Niemand et al. (2015) point out in their study on the freemium effect, a positive attitude towards the service strengthens one's intention to accept the offer, while a negative attitude will weaken it. According to Hamari et al. (2020), attitude towards freemium price models is a significant factor in the relationship between perceived value dimensions, as well as use and purchase intentions. These attitudes can be either negative or positive.

Examining willingness to pay for music services, Wagner & Hess (2013) stated that users' attitude towards the premium version is positively related to their intention to use the premium version. In the same context, Turkay et al. (2020) indicated a positive correlation between a consumer's attitude toward a premium version and their intention to pay for it. The authors also examined the attitudes regarding free versions and found that those with a positive attitude toward premium were twice as likely to be willing to pay for it than those with a negative attitude toward free versions. Other studies on music services (Mäntymäki et al., 2020; Wagner et al., 2014) also suggest that people's attitudes toward the premium version are a good predictor of whether they will purchase it. Thus, the following hypothesis is suggested.

> H5. Attitude toward premium apps has a positive effect on the intention to switch to premium applications.

2.2.6. The availability of free alternatives

This is fact that even when users are satisfied and not regretful with their existing service providers, they may still switch to another option because of its availability and attractiveness (Chang et al., 2014).

The presence of alternatives can benefit consumers by offering more choice, but it can also present challenges, including the potential to discourage consumer loyalty. If they are unaware of attractive alternatives, consumers also feel the need to stick with their current option (Chang et al., 2014). Chang et al. (2017) discuss the issue in the context of shopping channel switching behavior, explaning the alternative availability of different channels to shop and attractiveness of mobile retail shops due to convenience.

Alternative attractiveness is positively related to switching intention in the PPM framework (Liao et al., 2021; Marx, 2025). Mohd-Any et al. (2024) refer to this relation in cloud storage services. In freemium pricing context, it is a key indicator of user conversion rates (Phan Trong & Vo Thi Ngoc, 2024).

The reverse is true if there are free alternatives to premium services. When a better expected outcome is anticipated, individuals often switch to the alternative. In the context of mobile apps, Hsu & Lin (2015) propose that free alternatives to paid apps could serve as a substitute and potentially hinder users' continued use of paid apps. It is because when comparing options, consumers compare them in terms of quality and prices. Especially if the next price is zero, it will be easier to swtich with no financial risks. The authors also stated that free products speed up the decision-making process because they do not require people to think about how much they will spend. In app markets, the availability of free alternatives reduces consumers' motivation to pay for an app. This is true even when higher-performance paid versions are available. Accordingly, the following is proposed.

> H6. The availability of free alternatives has a negative effect on the intention to switch to premium applications.

2.2.7. Free mentality

People tend to avoid paying for online content. O'Brien (2022) defined free mentality as "the consumer's aversion to accept any price point other than zero". In a study investigating consumers' payment intentions for online news, the author confirmed the role of the free mentality on public's low payment intentions.

Some researchers even stated that the free mentality is the most important challenge for paid content sites. This is because people have become used to getting free information since the start, based on the idea that the Internet was originally meant to share information, and instead of customers paying for online content, advertisers should pay for it (Dou, 2004).

Free mentality was investigated in a variety of context such as software (Niemand et al., 2015), freemium games (Hamari et al., 2020), video streaming (Niemand et al., 2019), individual cloud services (Yan & Wakefield, 2018), and digital journalism (O'Brien, 2022).

The existence of free alternatives is not synonymous with a free mentality. The presence of free alternatives can lead to an increase in competition. However, the free mentality refers to the belief that all content should be free and universally accessible. The free mentality is the belief that all alternatives should be free of charge. Hüttel et al. (2018) mentioned to expect a price of zero to elicit overly positive feelings, which will affect consumer choices, even for e-services.

According to Yan & Wakefield (2018), there is a negative relationship between the willingness to pay for cloud services and free mentality. Lin et al. (2013) refered to a direct and negative impact of free mentality on attitude toward paying for online music services. Thus, the following hypothesis is suggested.

H7. Consumers' free mentality has a negative effect on the intention to switch to premium applications.

2.2.8. Price-quality inference

An individual difference, such as a free mentality, price-quality inference is stated as a research interest in consumer behavior. Niemand et al. (2019) defined the term as "the tendency to intuitively expect a positive relationship between price and quality, i.e., value". Another definition is "a thinking according to which fees serve as a signal to higher quality of the digital product or service" which is a concept derived from "price signaling." In other words, the price of paid content signals higher quality to potential subscribers (Pauwels & Weiss, 2008).

Niemand et al. (2019) investigated the role of the aforementioned variables on free versus premium preferences. They suggest that when these two factors are in conflict as opposing forces, it can lead to a reduction in consumer interest due to cognitive dissonance. In instances of minimal conflict, such as those involving high free mentality and low price-quality inference, the preference of free is more prominent (Biraglia et al., 2022).

According to Hsu et al. (2024), consumers switching to premium services still require further research attention due to inconsistent results of empirical studies. Regarding music streaming service conversion, Seifert et al. (2024) proposed that developers could decrease the benefits of the free version to make users dissatisfied with its value. This is because high enjoyment is said to decrease the intention to pay. Free users also overestimate the value of the free version due to the zero-price effect (Niemand et al., 2015). In contrast, the insurance, taximeter, and overestimation effects motivate consumers to subscribe to premium services (Lambrecht & Skiera, 2006), despite not using most premium service features (flat-rate bias). Wang et al. (2018) declared that if consumers believe they would gain more desirable benefits from using GPS navigation apps than from other options when comparing the price they pay, they should prefer to purchase the app because of its perceived value and necessity. Accordingly, the following is proposed.

H8. Consumers' price-quality inference has a positive effect on the intention to switch to premium applications.

2.2.9. Privacy concern

Companies collect customer information for several purposes: to better understand markets, to customize services and environments, to provide free services through affiliations with other businesses, and more. This information includes geo-locations, personal information such as dates of birth, and consumption-related information. However, this also increases consumers' concerns about their privacy. Some consumers perceive this action as intrusive. They also see it as an abuse of their personal information by unathorized access and use (Cosmo et al., 2021). Today, privacy concerns in digital environments are the topic of discussion.

Privacy concern in online is consumers' perceptions of how the information they provide online will be used, and if this use is fair. Companies must consider this concern to develop strategies matching the users' valuations. Due to today's pervasive data collection practices, privacy concerns are in a raising trend (Mahmoodi et al., 2018). Tsai et al. (2011) investigated Internet users' valuations of three privacy aspects commonly captured in social networking service privacy policies: data collection, data control, and third party sharing. The authors demonstrated that people are willing to pay a premium to purchase from websites that offer greater privacy protection when sufficient privacy information is available. The authors researched low-priced products and found that people were willing to pay up to 4% (around US$0.60) more for enhanced privacy. Egelman et al. (2013) demonstrated that 25% of smartphone users would be willing to pay a US$1.50 premium to use a mobile app that made fewer data requests.

However, another debate is that people may be willing to share information online despite having privacy concerns. This phenomenon is known as the “privacy paradox” (Norberg et al., 2007). This paradox has also been studied in the context of social networks. It is referred to as the result of a trade-off: using digital services (for free or not) in exchange for disclosing information. Thus, privacy and data are regarded as commodities traded between parties. Since willingness to pay is a measure of marketing activities for commodities, it can be used to evaluate data disclosure and privacy. The studies also included inquiries into customers’ experiences with privacy violations, such as breaches or hacks. In the absence of such experiences, individuals may not fully comprehend the significance of privacy, leading to an undervaluation of it. In cases involving identity theft, for example, the experience is particularly valuable because the results are more clearly defined (Mahmoodi et al., 2018). Consumers who perceive privacy risks are less likely to register with mobile apps and are reluctant to provide personal information (Kang & Namkung, 2019). It is also explained in relation to consumers’ control of information and their knowledge of privacy laws and the processing of personal data. Cosmo et al. (2021) examined the relationship between privacy concerns and the intention to use chatbots. The researchers hypothesized that privacy concerns would influence people’s attitudes toward chatbots and their intention to use this technology. Tsai (2023) mentioned earlier research on the idea that people might stop using services because of privacy concerns. Thus, the following hypothesis is suggested.

> H9. Consumers’ privacy concern has a negative effect on the intention to switch to premium applications.

2.2.10. Intention to switch to premium applications and moderating role of application (software) type

Ye & Potter (2011) refer intention to switch as product discontinuation. The concept is generally defined as the desire for the subsequent option. In the PPM framework, switching intention is examined in relation to a variety of push, pull, and mooring factors. Due to the relatively low switching costs associated with apps, it is essential to ensure that users are fully engaged with the app in order to encourage user retention. In contrast, the impact of migration from push and pull factors may be less significant (Gu et al., 2020). This could also be a reference to the importance of incorporating mooring factors into models with their direct relations and as moderator variables.

In order to develop a campaign that will appeal to potential users and attract users from competitors, it is essential to understand consumers’ intentions to switch between options (Chen et al., 2023).

Consumers’ propensity to switch may vary based on the category of mobile applications. This research shows that there is a gap in the research on comparing apps. Few studies directly compare different types in their proposed research models.

Wang et al. (2018) mentioned the rapid development of apps covering a wide variety of product and service categories. These categories include hedonic apps, such as games, music, media, and entertainment, as well as utilitarian apps, such as news, magazines, utilities, productivity, and navigation. In their study, the authors focused on GPS navigation apps and mentioned some research indicating that utilitarian apps are better at engaging and satisfying consumers than hedonic apps.

Hsu & Tsai (2017) investigated freemium pricing strategies in software as a service (SaaS) by categorizing them as either productivity or pleasure-oriented, according to the marketing research concepts of hedonic and utilitarian. They used the Unified Theory of Acceptance and Use of Technology (UTAUT) model, and defined the variables in different contexts to understand the differences in willingness to pay. For example, performance expectancy in productivity-oriented SaaS services is defined as the extent to which an individual believes using the system or software will improve his or her job performance. Conversely, in pleasure-oriented SaaS services it is defined as the extent to which these services enable users to fulfill certain tasks, such as relaxing or communicating with friends more effectively. A study by Nandi et al. (2021) examined the impact of perceived interactivity, and perceived value on mobile app stickiness. The researchers found that respondents anticipated different combinations of interactivity dimensions based on the purpose of the app. For instance, some individuals prefer applications for work-related communication due to their rapid and efficient nature. In the case of a productivity-related application, the presence of animations or emoticons is of little concern. However, if the application is related to communication or social media, the inclusion of such features is essential.

The concept of perceived value, which encompasses utilitarian value and hedonic value, is proposed as a driving force behind app usage. However, users value mobile applications differently, with some using them for productivity and or for entertainment. Social networking apps such as Facebook facilitate the exchange of information through text, images, video, and audio via mobile devices. For instance, social influences, such as social norms and social identification, have a significant role in determining a user's intention to use apps and make in-app purchases (Hsu & Lin, 2016). In their study of app users, Sánchez-Fernández & Iniesta-Bonillo (2009) identified four types of value, which are also evident in the variety of app categories, such as problem-solving apps (including productivity, financial planning, travel arrangement), entertainment and leisure apps (games, music, videos, etc.), social networking, and communication apps (Facebook, etc.), and information and others (shopping apps and news, etc.). Tyrväinen & Karjaluoto (2024) highly advised comparing the effect of perceived value on trust and willingness to pay a premium between two types of services: hedonic and utilitarian. Additionally, Guo (2022) notes that video streaming consumption is influenced more by hedonic than utilitarian values. Thus, it is apparent that not only do mobile applications differ in nature, but consumers' wants, expectations, and tolerances towards use may also differ.

> H10. Application type moderates all relationships among variables in the research model.

The research model was conceptualized using the PPM framework to understand the switching intentions of young adults. Figure 1 shows the research variables in relation to the focus of interest: intention to switch.

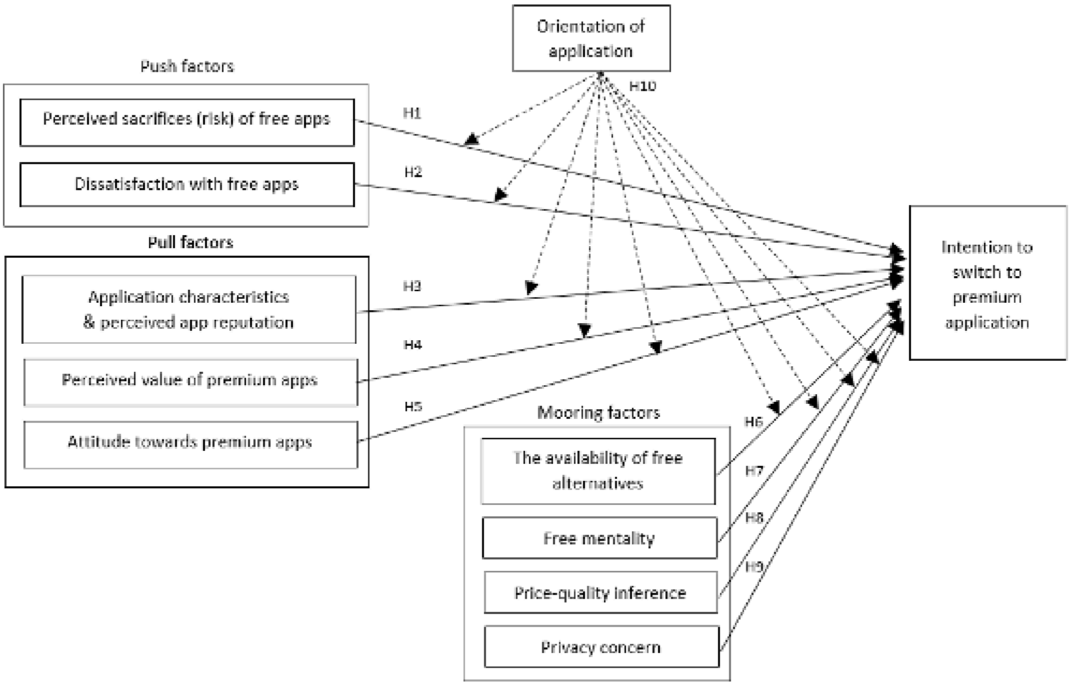

Figure 1. Research Model

3. Methodology

This research received ethical approval from the Istanbul University Social and Humanities Research Ethics Committee (Date: 28.04.2025, No: 04).

3.1. Measures

The proposed hypothesis on the effect of push-pull and mooring factors on switching intention was examined using a quantitative method. The data is collected using a survey method. The questionnaire is divided into three parts: the first part begins with filtering questions to filter respondents by age and usage of mobile apps, the second part contains scales for measuring the variables, and the last part includes multiple choice and open-ended questions to collect respondents' demographic information and their preferences regarding mobile service consumption, such as the monthly and annual amount of payment to mobile apps. All measurement items for each variable were derived from prior research. In the interest of clarity and unambiguity, the translation-back translation technique (Oquendo et al., 2001) was employed. In order to assess the relationships that were hypothesized, a series of constructs were examined and adapted for the purposes of this research. The Perceived Sacrifices (Risk) Scale was adapted from Kleijnen et al. (2007) based on Stone & Grnhaug (1993). The scale for measuring dissatisfaction was derived from the work of Mohd-Any et al. (2024). The application characteristics and perceived positive reputation were measured by the same-labeled scales employed by Harris et al. (2016) and based on the scale Hsu & Lin (2015) used for scaling the app rating. The concept of perceived value was adapted from Hsu & Lin (2016) with further refinement based on a comprehensive review of extant literature on consumer values. The attitude scale was adapted from Kim et al. (2017), which was based on Voss et al. (2003). The scale for the availability of free alternatives was adapted from Hsu & Lin (2015). The Free Mentality Scale was developed based on the work of Hsu et al. (2024) and Niemand et al. (2019). Price-Quality Inference was derived from the study of Niemand et al. (2019) once more. The measurement of privacy concern was adapted from the studies of Mani & Chouk (2017) and Malhotra et al. (2004). Finally, the switching intention scale is drawn from the works of Mohd-Any et al. (2024) and Sun et al. (2017). Appendix 1 details the 10 variables used in this study and their respective 59 measurement items. All scales were measured using a Likert scale of 1–5, with 5 indicating 'strongly agree' and 1 indicating 'strongly disagree', except for attitude scale which is measured as in the original scale, with bipolar adjectives, such as "(...) Very Necessary-Not Necessary at All".

3.2. Sample and data collection

Data were collected through an online questionnaire. In May 2025, a self-administered survey was circulated to a group of respondents using a convenience sampling method over a five-week period. The online survey was administered via a Google Docs form. Of the 260 responses received, those who reported not using mobile apps were excluded. After checking for outliers in the data, 239 valid questionnaires were used for further analysis. The sample profile is presented in Table 1.

Table 1. Characteristics of the Survey Sample

Characteristics	N	%	Characteristics	N	%
Gender			**Operating system**		
Female	112	46.9	Android	77	32.2
Male	127	53.1	IOS	162	67.8
Age			**Daily use of mobile devices**		
18-19	8	3.3	Less than 1 hour on average	1	0.4
20-21	81	33.9	1-3 hours on average	55	23.0
22-23	92	38.5	3-5 hours on average	101	42.3
24-25	32	13.4	5-7 hours on average	64	26.8
26-27	7	2.9	7 hours and above	18	7.5
28-29	10	4.2	**Monthly spending for mobile services (Turkish Liras)**		
30	9	3.8	0-100	84	35.1
Education			101-200	45	18.8
High School	155	64.9	201-300	33	13.8
Bachelor's Degree	78	32.6	301-400	11	4.6
Master's Degree/Doctorate	6	2.5	401-500	26	10.9
Monthly Income (Turkish Liras)			501-600	8	3.3
0 – 20,000	33	13.8	601 and above	32	13.4
20,001 – 40,000	42	17.6	**Annual spending for mobile services (Turkish Liras)**		
40,001 – 60,000	28	11.7	0-1,000	108	45,2
60,001 – 80,000	29	12.1	1,001-2,000	54	22,6
80,001 – 100,000	39	16.3	2,001-3,000	24	10,0
100,001 – 120,000	20	8.4	3,001-4,000	13	5,4
120,001 – 140,000	13	5.4	4,001-5,000	13	5,4
140,001 – 160,000	14	5.9	5,001-6,000	9	3,8
160,001 – 180,000	4	1.7	6,001-7,000	4	1,7

Characteristics	N	%	Characteristics	N	%
180,001 and above	17	7.1	7,001 and above	14	5.9

The total sample consists of young consumers between the ages of 18 and 30 (Table 1). A total of 153 respondents mentioned hedonic apps (social, games, etc.) as the most used category, while the utilitarian apps (productivity, tools, navigation, etc.) comprised 86 respondents. The filter question at the beginning of the survey excluded those above or below these ages. The sample consists of 47% women and 53% men. The age range is predominantly within the range representing young adults, specifically between 18 and 25 years old. The sample characteristics also include information on mobile device and mobile application usage. Accordingly, a significant majority spend at least 3 hours or more per day on their mobile devices, and the vast majority spend at least up to 200 TL per month (54%). In terms of annual spending, 45% spend at least up to 1,000 TL. This study categorizes apps as either hedonic (pleasure-oriented) or utilitarian (productivity-oriented). The sample was divided into these categories based on which category was used the most.

3.3. Data Analysis and Results

This empirical study used SmartPLS 4 for model testing and moderator analysis. This is due to the exploratory nature of the study, as in PPM studies, the framework is shaped around the research idea and modeled accordingly. The PLS technique is said to be best suited for PPM studies with complex models because it has minimal restrictions (Chang et al., 2014).

The PLS method shares commonalities with multiple regression analysis, as both aim to explain variance in outcome variables and evaluate the quality of the model based on psychometric attributes of the measurement and structural models (Ribeiro et al., 2023). PLS is a structural equation modeling (SEM) technique that can accommodate a significant number of variables, relationships, and moderating effects with small sample sizes. It makes no distributional assumptions and can handle constructs measured with single- and multi-item measures (Hair et al., 2021). It is recommended to use PLS-SEM when the analysis involves testing a theoretical framework from a predictive standpoint (Hair et al., 2021).

3.3.1. Common Method Bias

Common methos bias (CMB) is an issue that is likely to occur when evaluating data obtained from self-reported items (Singh & Kathuria, 2023; Thi Nguyet Trang et al., 2025). In this study, CMB is controlled with some precautions such as respondents were being assured of their anonymity and research confidentiality with mentioning the academic purposes, and that there were no right or wrong.

The most important thing was to provide honest answers to the questions, thinking of social desirability bias. Then, Herman's single factor analysis and the VIF values (Kock, 2015) are used to test for common method bias. According to Herman's single factor analysis, factor analysis in SPSS with factors to extract set to 1 reveals that the maximum variance explained by a single factor is 15.662%, which is below 50%. Therefore, it can be concluded that CMB is not a concern (Podsakoff et al., 2024). VIF for all constructs (see Table 2 and Table 7) were in the acceptable range below the threshold of 3 (Hair et al., 2019). Collinearity analysis confirmed the absence of CMB, thereby enhancing the robust nature of the model results.

3.3.2. Measurement Model Assessment

The measurement model was validated through indicator loadings, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2021). As outlined in Hair et al. (2019), all the outer loadings were above 0.708 and significant at a 1% level. Concurrently, all AVE values exceeded 0.50, which indicates satisfactory levels of convergent validity. The VIF values, a measure of the degree of multicollinearity, were found to be less than three, the commonly accepted ideal threshold value. These findings imply that the structural model does not exhibit any undesirable effects and is free from multicollinearity across items or predictor constructs. (see Table 2).

Table 2. Item loadings, convergent validity and collinearity statistics

Construct	Items	Loadings			Average Variance Extracted (AVE)			Variance Inflation Factor (VIF)		
		Overall Sample	Hedonic	Utilitarian	Overall Sample	Hedonic	Utilitarian	Overall Sample	Hedonic	Utilitarian
PPROF					0.754	0.742	0.769			
	PROF1	0.847	0.837	0.863				1.873	1.748	2.147
	PROF2	0.896	0.900	0.885				2.203	2.111	2.393
	PROF3	0.861	0.846	0.882				1.900	1.892	1.886
PSROF					0.760	0.727	0.829			
	PROF6	0.976	0.961	0.987				1.540	1.352	2.111
	PROF7	0.753	0.728	0.828				1.540	1.352	2.111
DWF					0.811	0.811	0.815			
	DWF1	0.884	0.880	0.895				2.426	2.391	2.602
	DWF2	0.931	0.941	0.913				3.168	3.496	2.836
	DWF4	0.887	0.879	0.900				2.337	2.423	2.322
AC					0.848	0.863	0.827			
	AC1	0.924	0.899	0.922				1.941	2.189	1.753
	AC2	0.917	0.959	0.896				1.941	2.189	1.753
PR					0.627	0.585	0.651			
	AC10	0.798	0.699	0.847				1.655	1.774	1.443
	AC8	0.771	0.842	0.770				1.196	1.137	1.405
	AC9	0.807	0.747	0.803				1.738	1.837	1.570
QV					0.783	0.787	0.776			
	QV1	0.925	0.932	0.926				2.181	2.105	2.363
	QV2	0.874	0.889	0.838				2.785	2.799	2.784
	QV3	0.855	0.838	0.876				2.835	2.764	2.978
PV					0.813	0.807	0.822			
	PV1	0.875	0.879	0.874				2.109	2.126	2.211
	PV2	0.919	0.921	0.911				2.423	2.724	2.013

Note: *PPROF: Perceived performance risk of free apps, PSROF: Perceived security risk of free apps, DWF: Dissatisfaction with free apps, AC: Application characteristics, PR: Positive reputation, QV: Quality value, PV: Price value, EV: Emotional value, ATP: Attitude towards Premium apps, AOFA: Availability of free alternatives, FM: Free mentality, PQI: Price-quality inference, PC: Privacy concern, SI: Switching intention.*

In the overall sample and for each group, Cronbach's Alpha (α) met the threshold of at least 0.70 and/or 0.60 in exploratory research, as required. As shown in Table 3, the composite reliability (CR) scores met the threshold of 0.70. This indicates that the measurement model is reliable and free of errors.

Table 3. Construct reliability

Construct	Cronbach's alpha			CR (rho_c)		
	Overall Sample	Hedonic	Utilitarian	Overall Sample	Hedonic	Utilitarian
Perceived performance risk of free	0.837	0.827	0.851	0.902	0.896	0.909
Perceived security risk of free	0.744	0.676	0.841	0.862	0.839	0.906
Dissatisfaction with free	0.883	0.883	0.887	0.928	0.928	0.930
Application characteristics	0.821	0.849	0.792	0.918	0.927	0.905
Positive reputation	0.708	0.690	0.736	0.835	0.808	0.848
Quality (performance) value	0.869	0.875	0.861	0.916	0.917	0.912
Price value	0.885	0.881	0.892	0.929	0.926	0.933
Emotional value	0.886	0.892	0.870	0.929	0.932	0.920
Attitude towards premium	0.886	0.866	0.908	0.884	0.877	0.899
Availability of free alternatives	0.774	0.760	0.804	0.868	0.862	0.880
Free mentality	0.747	0.774	0.694	0.863	0.896	0.846
Price-quality inference	0.828	0.811	0.842	0.896	0.884	0.904
Privacy concern	0.833	0.828	0.841	0.900	0.898	0.904
Switching intention	0.911	0.913	0.907	0.944	0.945	0.941

Discriminant validity was assessed by applying three methods: the correlations' Fornell-Larcker Criterion and the heterotrait-monotrait ratio (HTMT) (Henseler et al., 2015) and the examination of cross-loadings (Hair et al., 2021).

Table 4. Discriminant validity (Overall sample)

Construct	01	02	03	04	05	06	07	08	09	10	11	12	13	14
01.PPROF	**0.868**	0.545	0.386	−0.011	0.199	0.006	0.148	0.105	−0.044	−0.013	0.057	0.362	0.155	0.361
02.PSROF	0.649	**0.872**	0.122	0.042	0.186	0.152	0.132	0.090	0.006	0.050	0.115	0.228	0.340	0.239
03.DWF	0.447	0.122	**0.901**	−0.080	0.114	−0.020	0.144	0.085	−0.045	0.032	0.056	0.411	0.044	0.363
04.AC	0.074	0.106	0.092	**0.921**	0.382	0.239	0.126	0.192	0.085	0.158	0.035	0.016	0.197	0.107
05.PR	0.257	0.262	0.149	0.495	**0.792**	0.087	0.224	0.200	0.055	0.054	0.068	0.202	0.281	0.279
06.QV	0.039	0.194	0.086	0.294	0.126	**0.885**	0.424	0.568	0.161	0.134	0.132	0.148	0.231	0.224
07.PV	0.170	0.164	0.163	0.147	0.277	0.486	**0.902**	0.519	0.189	−0.078	−0.056	0.298	0.163	0.461
08.EV	0.119	0.097	0.092	0.230	0.249	0.652	0.579	**0.901**	0.201	0.002	0.061	0.266	0.171	0.293
09.ATP	0.104	0.044	0.112	0.139	0.061	0.187	0.159	0.237	**0.812**	−0.107	−0.066	0.129	0.021	0.179
10.AOFA	0.149	0.090	0.118	0.203	0.116	0.190	0.096	0.056	0.156	**0.829**	0.359	0.092	0.167	−0.083
11.FM	0.185	0.175	0.167	0.033	0.137	0.152	0.075	0.067	0.106	0.465	**0.873**	0.000	0.229	−0.119
12.PQI	0.431	0.242	0.469	0.021	0.260	0.163	0.346	0.307	0.111	0.112	0.059	**0.861**	0.196	0.407
13.PC	0.189	0.386	0.069	0.237	0.380	0.273	0.190	0.205	0.060	0.208	0.280	0.239	**0.867**	0.102
14.SI	0.413	0.239	0.403	0.123	0.340	0.232	0.512	0.321	0.114	0.097	0.119	0.454	0.117	**0.922**

Note: *Diagonal elements (in bold) represent square root of AVE value for the corresponding construct, the values above the diagonal indicate Fornell-Larcker results, and the values below indicate HTMT values.*

According to the Fornell-Larcker criterion, the on-diagonal values (the square root of the AVE) in the model above should be higher than the off-diagonal values. Additionally, the HTMT ratio should have a value smaller than 0.9 to confirm discriminant validity (Hair et al., 2021; Henseler et al., 2015).

Table 5. Discriminant validity (Hedonic)

Construct	01	02	03	04	05	06	07	08	09	10	11	12	13	14
01.PPROF	**0.862**	0.478	0.387	0.026	0.142	−0.027	0.053	0.064	0.046	−0.051	0.026	0.272	0.096	0.347
02.PSROF	0.584	**0.853**	0.092	0.091	0.110	0.055	−0.094	−0.045	0.115	0.045	0.058	0.096	0.303	0.200
03.DWF	0.454	0.143	**0.901**	−0.158	0.081	−0.082	0.063	0.014	−0.032	−0.015	0.071	0.453	−0.033	0.378
04.AC	0.084	0.209	0.192	**0.929**	0.369	0.321	0.162	0.254	−0.048	0.097	0.068	−0.053	0.234	0.039
05.PR	0.180	0.310	0.133	0.468	**0.765**	0.072	0.238	0.190	0.033	−0.084	0.011	0.112	0.218	0.195
06.QV	0.093	0.078	0.156	0.396	0.141	**0.887**	0.369	0.546	0.203	0.162	0.083	0.109	0.211	0.206
07.PV	0.091	0.122	0.089	0.195	0.259	0.420	**0.898**	0.525	0.283	−0.185	−0.173	0.162	0.043	0.483
08.EV	0.087	0.078	0.055	0.303	0.246	0.627	0.582	**0.906**	0.249	−0.021	−0.067	0.174	0.124	0.300
09.ATP	0.068	0.132	0.109	0.044	0.090	0.245	0.288	0.282	**0.803**	−0.169	−0.208	0.179	0.025	0.213
10.AOFA	0.177	0.099	0.128	0.121	0.138	0.219	0.231	0.062	0.213	**0.822**	0.397	0.070	0.166	−0.218
11.FM	0.138	0.082	0.188	0.076	0.112	0.124	0.224	0.080	0.180	0.516	**0.901**	−0.080	0.219	−0.257
12.PQI	0.330	0.150	0.525	0.060	0.135	0.133	0.176	0.196	0.197	0.094	0.095	**0.847**	0.047	0.314
13.PC	0.146	0.379	0.117	0.283	0.338	0.252	0.078	0.153	0.067	0.212	0.268	0.072	**0.864**	−0.080
14.SI	0.396	0.221	0.420	0.048	0.216	0.206	0.531	0.325	0.153	0.261	0.298	0.338	0.092	**0.923**

Note: *Diagonal elements (in bold) represent square root of AVE value for the corresponding construct, the values above the diagonal indicate Fornell-Larcker results, and the values below indicate HTMT values.*

Table 4, Table 5 and Table 6 show acceptable discriminant validity based on overall sample for both criteria and data from two groups. The discriminant validity of the measurement models appears to be well established, according to the findings.

Table 6. Discriminant validity (Utilitarian)

Construct	01	02	03	04	05	06	07	08	09	10	11	12	13	14
01.PPROF	**0.877**	0.623	0.383	−0.011	0.292	0.080	0.313	0.200	−0.120	−0.002	0.306	0.447	0.228	0.364
02.PSROF	0.734	**0.911**	0.156	0.027	0.253	0.330	0.499	0.334	−0.106	0.052	0.279	0.393	0.395	0.292
03.DWF	0.442	0.141	**0.903**	0.035	0.221	0.107	0.292	0.224	−0.069	0.058	0.173	0.357	0.175	0.336
04.AC	0.097	0.100	0.074	**0.909**	0.473	0.117	0.073	0.085	0.231	0.282	−0.017	0.119	0.155	0.238
05.PR	0.362	0.269	0.279	0.601	**0.807**	0.097	0.268	0.207	0.150	0.306	0.207	0.334	0.368	0.470
06.QV	0.110	0.377	0.127	0.144	0.110	**0.881**	0.545	0.607	0.097	0.070	0.285	0.256	0.278	0.284
07.PV	0.358	0.536	0.324	0.088	0.328	0.618	**0.906**	0.529	0.055	0.083	0.274	0.519	0.385	0.443
08.EV	0.233	0.380	0.255	0.104	0.275	0.705	0.589	**0.891**	0.129	0.051	0.311	0.462	0.284	0.314
09.ATP	0.200	0.182	0.128	0.313	0.160	0.103	0.086	0.162	**0.833**	−0.004	0.099	0.109	0.043	0.162
10.AOFA	0.118	0.091	0.142	0.312	0.385	0.142	0.126	0.094	0.139	**0.844**	0.255	0.087	0.163	0.162
11.FM	0.312	0.354	0.192	0.138	0.278	0.341	0.292	0.425	0.180	0.384	**0.858**	0.179	0.225	0.227
12.PQI	0.533	0.445	0.398	0.147	0.431	0.295	0.596	0.540	0.095	0.137	0.202	**0.870**	0.413	0.540
13.PC	0.267	0.402	0.203	0.193	0.454	0.324	0.443	0.334	0.079	0.214	0.300	0.494	**0.872**	0.423
14.SI	0.411	0.262	0.373	0.278	0.559	0.300	0.479	0.349	0.110	0.166	0.247	0.601	0.478	**0.918**

Note: *Diagonal elements (in bold) represent square root of AVE value for the corresponding construct, the values above the diagonal indicate Fornell-Larcker results, and the values below indicate HTMT values.*

Another criterion for checking the discriminant validity of the measurement models is to use cross-loading results. Tables Appendix 2, Appendix 3, and Appendix 4 in the Appendix detail the data; the bold values relate to the measures of the specific constructs in the rows. As can be seen, the constructs' measures share a higher correlation within than with the other measures.

3.3.3. Assessment of structural model and hypotheses testing

The structural model was assessed through PLS using Smart-PLS 4, including the evaluation of path coefficients, coefficient of determination (R^2), predictive relevance values (Q2), and statistical significance. This study performed 5,000 bootstrap resampling iterations on two samples.

Table 7 shows that the overall sample has an R^2 value of 0.411, hedonic app users have an R^2 value of 0.493, and utilitarian app users have an R^2 value of 0.462. These values are considered moderate in terms of explanatory power. According to Hair et al. (2019), any Q2 value above zero is meaningful (for the overall sample and hedonic app users, the value of predictive accuracy is medium, while for productivity app users, it is small) and a well-model fit is indicated by an SRMR value lower than 0.12, which is evident in the results for both groups. VIF values are also below 3 for latent constructs.

Table 7. Structural model assessment

Variable		VIF (Overall sample)	VIF (Hedonic)	VIF (Utilitarian)
PPROF -> SI		1.779	1.600	2.317
PSROF -> SI		1.633	1.531	2.280
DWF -> SI		1.363	1.520	1.342
AC -> SI		1.302	1.401	1.470
PR -> SI		1.353	1.312	1.726
QV -> SI		1.731	1.716	1.987
PV -> SI		1.565	1.615	2.111
EV -> SI		1.804	1.802	1.989
ATP -> SI		1.098	1.249	1.178
AOFA -> SI		1.250	1.338	1.258
FM -> SI		1.231	1.321	1.394
PQI -> SI		1.474	1.434	1.922
PC -> SI		1.316	1.272	1.460
Structural Model	R^2	0.411	0.493	0.462
	Q^2	0.320	0.373	0.150
	SRMR	0.058	0.069	0.071

As seen in Table 8, the model demonstrates a significantly stronger predictive ability for hedonic app users than for utilitarian app users. The Q2 predicted values were also above 0. Predictive relevance is stronger again for hedonic app users.

Table 8. PLS predict results for predictive power of the model

Item	Overall Sample			Hedonic			Utilitarian		
	Q^2 predict	PLS-SEM_RMSE*	PLS-SEM_MAE*	Q^2 predict	PLS-SEM_RMSE*	PLS-SEM_MAE*	Q^2 predict	PLS-SEM_RMSE*	PLS-SEM_MAE*
SI1	0.270	0.987	0.784	0.308	0.937	0.767	0.091	1.145	0.939
SI3	0.288	0.999	0.796	0.316	0.972	0.760	0.225	1.053	0.889
SI4	0.255	0.999	0.802	0.325	0.967	0.774	0.044	1.075	0.846

Notes: *PLS-SEM_RMSE < LM_RMSE, PLS-SEM_MAE < LM_MAE*

The results showed that the price of premium apps, dissatisfaction with free apps, the perceived performance risk of free apps, the price-quality inference, the positive reputation of apps, and the free mentality impacted switching intention for both groups (see Table 9). For hedonic apps, perceived price value (β = 0.356, p = 0.000), dissatisfaction with free apps (β = 0.277, p = 0.001), perceived security risk of free apps (β = 0.189, p = 0.009), perceived performance risk of free apps (β = 0.125, p = 0.048), and perceived quality value (β = 0,124, p= 0.040) were positively related to the intention to switch, respectively. Furthermore, the free mentality (β = −0.117, p = 0.010) and privacy concern (β = −0.150, p = 0.044) were negatively related to the intention. For utilitarian apps, price-quality inference (β = 0.265, p = 0.026) and positive reputation (β = 0.220, p = 0.035) were positively related to the intention to switch.

Table 9. Effects, t-values and p-value

Effects		Overall Sample			Hedonic			Utilitarian			Supported
		Path Coefficients	t value	p value	Path Coefficients	t value	p value	Path Coefficients	t value	p value	OS/H/U
H1a	PPROF -> SI	0.152	2.348	0.009*	0.125	1.668	0.048*	0.158	1.136	0.128	Yes/Yes/No
H1b	PSROF -> SI	0.058	0.857	0.196	0.189	2.356	0.009*	−0.116	0.812	0.208	No/Yes/No
H2	DWF -> SI	0.205	3.097	0.001*	0.277	3.172	0.001*	0.092	0.924	0.178	Yes/Yes/No
H3a	AC -> SI	0.032	0.537	0.296	−0.008	0.107	0.457	0.038	0.342	0.366	No/No/No
H3b	PR -> SI	0.126	2.289	0.011*	0.060	0.901	0.184	0.220	1.807	0.035*	Yes/No/Yes
H4a	QV -> SI	0.085	1.318	0.094	0.124	1.751	0.040*	0.128	0.930	0.176	No/Yes/No
H4b	PV -> SI	0.277	3.641	0.000*	0.356	3.970	0.000*	0.129	0.923	0.178	Yes/Yes/No
H4c	EV -> SI	−0.008	0.129	0.449	0.028	0.394	0.347	−0.073	0.581	0.281	No/No/No
H5	ATP -> SI	0.092	1.147	0.126	0.006	0.077	0.469	0.088	0.677	0.249	No/No/No
H6	AOFA -> SI	−0.044	0.596	0.276	−0.073	1.050	0.147	0.020	0.160	0.436	No/No/No
H7	FM -> SI	−0.117	1.710	0.044*	−0.171	2.315	0.010*	0.007	0.055	0.478	Yes/Yes/No
H8	PQI -> SI	0.138	2.009	0.022*	0.051	0.691	0.245	0.265	1.950	0.026*	Yes/No/Yes
H9	PC -> SI	−0.050	0.743	0.229	−0.150	1,701	0.044*	0.147	1.131	0.129	No/Yes/No

Notes: **p < 0.05; OS: Overall Sample, H: Hedonic, U: Utilitarian.*

The objective of this study is to examine the factors that can influence Generation Z consumers' intention to switch from free apps to paid apps. Additionally, the study seeks to understand how intention to pay for apps differs based on the category of mobile apps. To this end, multigroup analysis (MGA) was conducted to assess the moderating effect of the orientation of the application.

The objective was to ascertain whether there are significant differences in path coefficients between hedonic and utilitarian app users.

Table 10. Results of invariance measurement testing (Step 1 & MICOM Step 2)

Construct	Configural invariance	Original correlation	5.0%	Permutation p-value	Compositonal invariance
PPROF	Yes	0.997	0.985	0.497	**Yes**
PSROF	Yes	0.998	0.718	0.823	**Yes**
DWF	Yes	0.999	0.992	0.713	**Yes**
AC	Yes	0.993	0.545	0.675	**Yes**
PR	Yes	0.961	0.898	0.247	**Yes**
QV	Yes	0.999	0.849	0.927	**Yes**
PV	Yes	0.997	0.996	0.100	**Yes**
EV	Yes	0.999	0.989	0.770	**Yes**
ATP	Yes	0.980	0.189	0.877	**Yes**
AOFA	Yes	0.987	0.142	0.900	**Yes**
FM	Yes	0.955	0.218	0.597	**Yes**
PQI	Yes	0.994	0.985	0.309	**Yes**
PC	Yes	1.000	0.364	0.995	**Yes**
SI	Yes	1.000	0.999	0.195	**Yes**

Prior to conducting multigroup analyses, the MICOM procedure was applied as an assessment to determine the measurement invariance of the model (see Table 10 and Table 11). An analysis of the invariance measure is conducted to guarantee that the measurement model is capable of identifying the same measurement attribute under varying conditions.

Table 11. Results of invariance measurement testing (MICOM Step 3)

Construct	Mean-Original difference	Mean Permutation p value	Confidence Interval (CI) 95%		Variance-Original difference	Variance Permutation p value	CI 95%		Equal mean Equal variance
PPROF	−0.284	0.030	−0.270	0.254	−0.235	0.233	−0.355	0.394	**No/Yes**
PSROF	−0.103	0.482	−0.264	0.257	−0.234	0.142	−0.278	0.337	**Yes/Yes**
DWF	−0.063	0.671	−0.262	0.286	−0.201	0.214	−0.312	0.334	**Yes/Yes**
AC	0.193	0.158	−0.263	0.259	−0.493	0.184	−0.677	0.703	**Yes/Yes**
PR	−0.172	0.200	−0.279	0.260	0.125	0.576	−0.404	0.421	**Yes/Yes**
QV	0.070	0.610	−0.261	0.284	0.189	0.526	−0.489	0.521	**Yes/Yes**
PV	−0.054	0.697	−0.267	0.273	0.004	0.984	−0.341	0.384	**Yes/Yes**
EV	0.126	0.343	−0.247	0.263	0.201	0.408	−0.467	0.447	**Yes/Yes**
ATP	0.183	0.172	−0.261	0.262	−0.359	0.092	−0.403	0.443	**Yes/Yes**
AOFA	0.012	0.928	−0.289	0.269	−0.190	0.331	−0.368	0.367	**Yes/Yes**
FM	−0.097	0.465	−0.247	0.233	0.141	0.447	−0.351	0.388	**Yes/Yes**
PQI	−0.302	0.028	−0.276	0.258	−0.344	0.029	−0.305	0.313	**No/No**
PC	−0.141	0.302	−0.262	0.254	0.076	0.693	−0.364	0.420	**Yes/Yes**

SI	−0.258	0.059	−0.260	0.268	0.008	0.947	−0.291	0.288	**Yes/Yes**

The PLS models, data treatment, and algorithm settings used for the groups were all the same. This means that the configural invariance was established (MICOM Step 1). To check the compositional invariance of the model (MICOM Step 2), the SmartPLS Permutation procedure was used. According to the results, the requirements for the first two steps of the three-step MICOM procedure (Henseler et al., 2016) were met. This means that partial measurement invariance was achieved. According to Sarstedt et al. (2022) and several other research using the method, this allows for multigroup analyses.

Table 12. Hypothesis testing of moderation of app orientation with multi-group analysis

Effects	Path Coefficient Difference	p value (Hedonic vs Utilitarian)			Support
		Henseler's-MGA	Parametric test	Welch-Satterthwaite test	
PPROF -> SI	−0.033	0.411	0.410	0.418	No
PSROF -> SI	0.305	**0.033**	**0.022**	**0.032**	Yes
DWF -> SI	0.184	0.081	0.091	0.083	No
AC -> SI	−0.045	0.358	0.359	0.365	No
PR -> SI	−0.159	0.125	0.106	0.126	No
QV -> SI	−0.004	0.487	0.490	0.491	No
PV -> SI	0.227	0.088	0.077	0.087	No
EV -> SI	0.101	0.236	0.224	0.242	No
ATP -> SI	−0.082	0.280	0.288	0.297	No
AOFA -> SI	−0.094	0.241	0.240	0.259	No
FM -> SI	−0.178	0.110	0.096	0.112	No
PQI -> SI	−0.214	0.078	0.065	0.084	No
PC -> SI	−0.297	**0.034**	**0.026**	**0.030**	Yes

The results of the multigroup analysis are shown in Table 12. The study identified two factors that differ between groups in terms of their impact on the intention to transition to paid apps: perceived security risks associated with free apps and consumers' privacy concerns. Since unequal variances were determined for some constructs, Welch-Satterthwaite test was also used as a basis. The p-values referring the significance of differences between paths were all below 0.05.

4. Conclusion

The primary aim of the research is to better understand consumers' intention to pay for apps. According to the results, which included responses from 239 people, the factors most influencing consumers' switching intention were identified as the price value of premium apps, dissatisfaction with free apps, perceived performance risk of free apps, price-quality inference, positive reputation of apps, and free mentality, respectively. Then, as part of the research questions, the orientation of apps was investigated to determine if it moderates the relationship between the antecedents of switching intention and the respective variable.

A comparison of hedonic (entertainment-oriented) and utilitarian (productivity-oriented) apps revealed significant differences in switching intentions influenced by security and privacy related concerns. The study found two factors that were different between groups in how they affected the desire to use paid apps. These factors were the perceived security risks of free apps and consumers' privacy concerns.

This study yielded valuable results through a comparison of the research model in different service contexts.

4.1. Discussion and theoretical implications

In this study, among push factors, dissatisfaction and perceived risk related to the performance of free apps are significant. Satisfaction with the existing offering is a common theme, and dissatisfaction with that offering is a frequent complaint. Negative experiences with the existing product offer can also motivate customers to consider alternatives (Krishnan & Raghuram, 2024). As one of the most frequently referenced variables in PPM studies, it is not surprising that dissatisfaction with free apps is creating meaningful differences in the selection of paid apps.

People are also motivated to choose paid apps by perceived performance risk or sacrifices relating to the output of utilities or apps. Normally, free or freemium services is helpful for reducing uncertainties of services. Hsu & Lin (2015) stated that free or freemium apps reduce the risk and uncertainty of purchasing an app, allowing consumers to become more familiar with the content. Depending on the monetization strategy (premium with fixed monthly payments after a free trial period, free with in-app purchases, etc.), people can choose how to unlock the value they will receive from the service. They can get more value in various forms, such as paying for additional benefits in performance or to remove ads included. On the contrary, with limited features or limited use time (Tyrväinen & Karjaluoto, 2024) perceptions on free/freemium service performances could be a concern. For hedonic apps, all push factors are significant, while for utilitarian apps, none are. This may signal that, in utilitarian free apps, dissatisfaction or risk perceptions are low, and these factors are not related to people's need to turn to paid apps in the research interets of young consumers. Performance risk is a concern for hedonic apps, and if users are dissatisfied, they will seek out paid versions. The perception of security risk also has been shown to have a positive impact on the intention to switch. On mobile apps, Dinsmore et al. (2017) stated that exploring the effects of different risk factors on purchasing behavior could be informative, considering the small financial risk associated with small fees compared to the significant privacy risk of purchasing a product online. Yang et al. (2022) included privacy risk to performance risk to understand how these variables relate to intentions to upgrade to paid online healthcare consultations. Therefore, it was determined that incorporating privacy/security risk perceptions into this study was an appropriate decision to ensure the comparability of results.

The factors that have the greatest impact on a user's intention to switch to paid apps are those related to price value. Mäntymäki et al. (2020) revealed the effects of price value, and enjoyment on switching intention to premium, accounting for differences in subscription type (basic vs. premium). The perceived value of a product or service is determined by the subtle differences in value judgments made by the users. For instance, millennials place greater value on smartphones than on traditional desktop or laptop computers or televisions, despite the latter's smaller screen size (Nandi et al., 2021). This study on young consumers revealed that price value is significant in the hedonic apps, along with quality/performance value.

People's concern for the positive reputation of apps attracts consumers and contributes to switching intentions in the utilitarian category. As Harris et al. (2016) stated the reputation of an application market or developer can be influenced by the actions and perceptions of others, including websites and friends. Thus, if consumers find a site reputable, they may trust the site more and perceive less risk.

As mooring factors, individual characteristics of free mentality and price-quality inference contribute to the intention to switch. In the hedonic app category, free mentality and privacy concerns are significant, while price-quality inference is significant for the utilitarian category.

As an important challenge for paid content sites, the free mentality has been an ongoing barrier since the introduction of the freemium-premium pricing concept. As prior studies (Lin et al., 2013; Yan & Wakefield, 2018) have mentioned, there is a negative relationship between willingness to pay for services and the free mentality. This effect is found to be significant for hedonic services in this study. The implementation of a paid model for content that was previously free would potentially lead to a sense of loss among consumers, as they would be comparing it to the prior, complimentary price point. This may be a result of a learned behavior where advertising based business models support free use in consumer markets such as radio, TV or the Internet (O'Brien, 2022). Therefore, the free mentality is a personal characteristic that should be included in this area of research.

In addition, price-quality inference is of considerable importance in the context of the utilitarian category. Niemand et al. (2019) discussed how consumers' responses to free offers are not thoughtful, but rather driven by intuition. As previously stated, people activate these intuitions, free mentality and price-quality inferences, during the decision-making process. Their study illustrated that user preferences are shaped not only by features. Intuitive thoughts about freemium offers also shape preferences. Thus, people who believe that high prices are linked to high quality tend not to choose free options. Even if they have favorable thoughts about the free option, they abandon it because of negative expectations about its quality and functionality.

Privacy concerns only affect switching intentions in the hedonic app category, just as security risk perceptions of free push users towards paid options in the same category. Boerman et al. (2017) explained privacy concerns with the help of social presence theory. Social presence is the feeling of being with someone else during mediated communication and if it's a computer or a mobile phone collecting the data, it feels the same as when someone looks over your shoulder as you browse. As posited by Harris et al. (2016), individuals may have privacy or security concerns regarding data that is not essential for app functionality and for which consumers must grant permission. If companies provide their customers with the proper information, they can potentially collect more consumer data without losing customers when they request in-app permissions. The authors studied the factors that influence consumers' decisions to install mobile apps. They stated that perceived security could decrease risk perceptions and increase trust in mobile apps.

Another interesting finding is that the perceived security risks of free apps and consumers' privacy concerns are variables that differ between groups in terms of their effects on the intention to switch; these effects are higher and significant for the hedonic app category. This may indicate that young consumers tend to behave similarly without the presence of security risks and/or when their privacy concerns are low, and that these are the only effects that differ by app category. This result is thought to provide a valuable foundation for further research.

4.2. Practical implications

One finding is that reducing performance risk perceptions is valuable in any mobile service context. The proper functioning of utilities offered by the mobile channel could help consumers become more satisfied. If not, with an increase in risk perception, users can choose to switch to a premium app.

Decreasing performance and security risk perceptions is also valuable for encouraging consumers to convert to premium apps, especially in the entertainment category. This category includes apps such as music, games, and social media. Information risks regarding security and privacy can be addressed through companies educating users and users asking companies to be more transparent, security-oriented, and to invest in security protocols. Games and social media also provide a platform for brands to display their advertisements and commercials. Thus, users of these apps need to be profiled based on personal characteristics or usage-based filters to provide a more customized service. Users should be aware that if they want to use free apps, they will have to provide contextually relevant information to companies. However, premium apps also collect data to provide superior services. If managed properly, consumers should not feel security risks when using mobile devices, whether free or paid.

Price value is the utility gained from the product that results from the reduction costs. The apps in the entertainment category provided more value for money, and, given their performance benefits, they had a significant pull effect to encourage paying for premium apps. It can be concluded that service providers in this category should prioritize value and quality. As these increase, so does the likelihood that people will pay for these apps.

The results regarding the relationship between a positive reputation and switching intention must be discussed in terms of their implications. This variable affects consumers' intention to pay in general and for a specific category. The utilitarian category includes tool apps, navigation apps, health apps, etc. These types of apps are especially chosen for utilitarian purposes. A reputation can be built upon many things, including utility, quality of service, and brand attributes. Today, with the integration of AI, as we have seen with chatbots, more consumers are incorporating them into their daily tasks. A well-known brand and a reputable service would be a significant advantage for an app of this nature, as it would likely attract users willing to pay for services.

Companies can practically do nothing to solve the issue of the free mentality. This is due to all the practices since the beginning of the internet and IT tech-enabled services. As mentioned, most apps are still free. However, by offering free and premium options together and setting meaningful prices with price fences for the premium options, consumers may be more willing to pay after trying them. Mobile service providers could leverage people's price-quality preferences much better by communicating the relative advantages.

Understanding privacy concerns is another obstacle. People's intentions and behavior contradict each other when they have concerns but still use the service. This is referred to as the "privacy paradox" in the literature (Norberg et al., 2007). Privacy and security could also be communicated as part of app providers' branding activities and service design processes.

4.3. Limitations and future research directions

The study's results highlight the importance of privacy/security risks on consumers' psychology when it comes to entertainment purposes. Further studies could investigate the reasons behind risk perceptions and satisfaction results in case these risks are actually higher due to the current implications of entertainment service providers in the mobile sector. Alternatively, it could be related to a broader selection of apps in an app category, such as in games, compared to utilitarian services. Another possibility is that it is due to people's interest and knowledge in different categories. Push variables and their antecedents need further attention.

Further research is necessary to investigate the negative correlation between free mentality and switching intention, as well as the reasons why it is a concern for entertainment services.

According to the results, the availability of free alternatives does not influence the intention to switch. Further research could investigate other relevant variables, such as the attractiveness of different alternatives. If there are relatively better alternatives than the free versions, the likelihood of switching can be higher. Of course, people's tendencies should also be modeled with control variables other than age, such as gender and income.

Social influences could also be added to a model when young consumers and different app categories are included. Social norms, or social value as part of value dimensions, could be a variable for further research. This would be particularly relevant if the market of interest is hedonic apps such as games.

Attitudes toward premium apps could also be a variable to focus on, not just for its direct effect on switching intention, but also for its mediating effects. Another proposition that the research could include is that perceived value affects attitudes, with another path that could be included in the model with a chain of effects between value, attitude, and behavior. According to Phan Trong & Vo Thi Ngoc (2024) study of the PPM framework in over-the-top (OTT) services, willingness to pay increases conversion intent from free to premium among freemium service users. Willingness to pay could be one of the factors to consider in future studies.

In a comparison of free and premium services, Tyrväinen & Karjaluoto (2024) address the differences between different monetization strategies, calling them "limited features" and "virtual items," and on willingness to pay, they use a multidimensional perspective of value that includes functionality, price, social, and hedonic dimensions. The authors proposed that perceived value would differ between the two strategies. Based on the findings of the study, further research may include a detailed comparison of app monetization strategies across different orientations.

Declarations

Ethics Committee Approval This research received ethical approval from the Istanbul University Social and Humanities Research Ethics Committee (Date: 28.04.2025, No: 04).

Conflict of interest The author(s) have no competing interests to declare that are relevant to the content of this article.

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Appendix

Appendix 1. Measures

Constructs		Constructs	Sources
Perceived Sacrifices (Perceived Risk)	PROF1	I worry about the performance of free apps.	Kleijnen et al. (2007); Stone & Grønhaug (1993)
	PROF2	I'm concerned that the benefits offered by free apps are insufficient.	
	PROF3	I'm concerned that free apps are not user-friendly in terms of performance.	
	PROF4	Free apps are often time-consuming because they contain ads.	
	PROF5	I'm concerned that free apps may not provide a secure service.	
	PROF6	I worry about the privacy of my personal information in free apps.	
	PROF7	Free apps share my information with other individuals/organizations to benefit advertisers.	
	PROF8	I worry about the security of my personal information in free apps.	
Dissatisfaction	DWF1	I've generally been dissatisfied with the free apps I've used in the past.*	Mohd-Any et al. (2024)
	DWF2	The free apps I've used haven't satisfied me.*	
	DWF3	I'm contended with my decision to use free apps.	
	DWF4	Free apps are never satisfying.*	
The Application Characteristics & Perceived Positive Reputation	AC1	It's important for an app to have a high rating.	Harris et al. (2016); Hsu & Lin (2015)
	AC2	It's important for an app to have positive user reviews.	
	AC3	It's important for an app to have a high number of downloads (popularity).	
	AC4	The storage space an app will take up is important.	
	AC5	The permissions requested when I want to download/use the app are important (camera, microphone, access to my contacts, etc.).	
	AC6	The extent to which the app meets my needs is important.	
	AC7	The extent to which the app contains ads is important.	
	AC8	It's important for the app to personalize the service for me.	
	AC9	The reputation of the app owner/brand is important.	
	AC10	It's important that I trust the app owner/brand.	
Perceived Value	QV1	The apps are well-designed.	Hsu & Lin (2015); Sweeney & Soutar (2001)
	QV2	The apps have an acceptable quality standard.	
	QV3	The apps offer consistent quality.	
	PV1	The app prices are reasonable.	
	PV2	The apps are value for money.	
	PV3	The app quality is good for the price.	
	EV1	Using the apps makes me feel relaxed.	
	EV2	I enjoy using the apps.	
	EV3	Using the apps makes me feel good.	
Attitude		*The premium version of the apps in this category is*	Kim et al. (2017); Voss et al. (2003)
	ATF1	(...) Very Necessary-Not Necessary at All	
	ATF2	(...) Very Useful-Not Useful at All	
	ATF3	(...) Very Beneficial-Not Beneficial at All	
	ATF4	(...) Very Good-Not Good at All	
	ATF5	(...) Very Fun-Not Fun at All	

Constructs		Constructs	Sources
	ATF6	(...) Very Enjoyable-Not Enjoyable at All	
	ATF7	(...) Very Attractive-Not Attractive at All	
The Availability of Free Alternatives	AOFA1	There are many free alternatives to paid apps in the app market.	Hsu & Lin (2015)
	AOFA2	Free alternatives to paid apps meet my needs.	
	AOFA3	Free alternatives to paid apps offer good quality.	
	AOFA4	I can find free alternatives to paid apps.	
Free Mentality	FM1	The internet should be free, so we shouldn't pay for any content.	Hsu et al. (2024); Niemand et al. (2019)
	FM2	Providing free content fits the internet's original purpose to provide information.	
	FM3	Advertisers, not users, should be paying for online content.	
	FM4	Online information or software should be free.	
	FM5	The price I pay for an application is important factor for me.	
Price-Quality Inference	PQI1	Generally, the higher the price of a product or service, the higher its quality.	Niemand et al. (2019)
	PQI2	The saying "You get what you pay for" generally rings true.	
	PQI3	The price of a product is a good indicator of its quality.	
Privacy Concern	PC1	I'm concerned about threats to the privacy of my personal information.	Malhotra et al. (2004); Mani & Chouk (2017)
	PC2	I refuse to provide requested personal information and leave the website/app.	
	PC3	It bothers me to give personal information so I distort information when providing it.	
	PC4	I do not accurately reflect my personal information.	
	PC5	I worry about the security of my personal information.	
Switching Intention	SI1	I would consider upgrading from the free app to the paid version.	Mohd-Any et al. (2024); Sun et al. (2017)
	SI2	I plan to upgrade from the free app to the paid version.	
	SI3	I would rather stop using the free app and opt for the paid version.	
	SI4	The chance of my switching to the paid app version in the future is high.	

Appendix 2. Discrimant Validity - Cross Loadings (Overall Sample)

	PPROF	PSROF	DWF	AC	PR	QV	PV	EV	ATP	AOFA	FM	PQI	PC	SI
PROF1	**0.847**	0.479	0.260	0.069	0.155	0.044	0.121	0.114	−0.011	0.015	0.013	0.386	0.171	0.292
PROF2	**0.896**	0.441	0.353	−0.022	0.180	−0.021	0.159	0.051	−0.089	−0.100	0.011	0.274	0.071	0.332
PROF3	**0.861**	0.504	0.388	−0.069	0.182	−0.005	0.105	0.112	−0.010	0.059	0.123	0.290	0.167	0.314
PROF6	0.548	**0.976**	0.154	0.005	0.185	0.150	0.126	0.098	0.014	0.042	0.110	0.244	0.348	0.264
PROF7	0.363	**0.753**	−0.014	0.140	0.132	0.110	0.107	0.040	−0.018	0.059	0.094	0.105	0.206	0.087
DWF1	0.351	0.131	**0.884**	−0.064	0.093	0.039	0.115	0.086	−0.077	0.057	0.063	0.337	0.051	0.307
DWF2	0.350	0.123	**0.931**	−0.103	0.098	−0.038	0.132	0.070	−0.017	0.022	0.078	0.362	0.019	0.347
DWF4	0.343	0.077	**0.887**	−0.047	0.116	−0.052	0.141	0.074	−0.032	0.011	0.010	0.412	0.051	0.324
AC1	−0.004	0.048	−0.109	**0.924**	0.355	0.244	0.134	0.185	0.095	0.144	0.047	0.012	0.181	0.101
AC2	−0.015	0.029	−0.037	**0.917**	0.349	0.195	0.097	0.168	0.060	0.148	0.016	0.017	0.182	0.096
AC10	0.145	0.222	0.013	0.339	**0.798**	0.114	0.142	0.120	0.030	0.046	0.098	0.137	0.307	0.211
AC8	0.158	0.016	0.145	0.303	**0.771**	0.042	0.211	0.184	0.024	0.025	0.016	0.169	0.118	0.255
AC9	0.170	0.243	0.102	0.259	**0.807**	0.054	0.169	0.168	0.087	0.062	0.055	0.173	0.270	0.184
QV1	0.023	0.108	0.045	0.172	0.082	**0.925**	0.381	0.518	0.171	0.108	0.109	0.170	0.186	0.259
QV2	−0.005	0.171	−0.033	0.281	0.102	**0.874**	0.351	0.486	0.108	0.134	0.141	0.114	0.223	0.160
QV3	−0.017	0.148	−0.123	0.213	0.041	**0.855**	0.409	0.511	0.133	0.124	0.109	0.080	0.225	0.132
PV1	0.140	0.138	0.159	0.094	0.185	0.383	**0.875**	0.412	0.173	−0.089	−0.072	0.258	0.125	0.394
PV2	0.166	0.085	0.125	0.123	0.203	0.408	**0.919**	0.524	0.162	−0.048	−0.011	0.294	0.174	0.453
PV3	0.091	0.139	0.106	0.123	0.217	0.353	**0.910**	0.460	0.179	−0.078	−0.074	0.251	0.138	0.397
EV1	0.150	0.091	0.108	0.122	0.172	0.497	0.506	**0.905**	0.198	−0.043	0.032	0.253	0.100	0.301
EV2	0.036	0.092	0.039	0.205	0.153	0.589	0.459	**0.905**	0.190	0.024	0.060	0.177	0.176	0.225
EV3	0.080	0.061	0.072	0.205	0.216	0.460	0.431	**0.894**	0.152	0.034	0.077	0.280	0.199	0.255
ATP1	−0.015	0.024	−0.007	0.055	0.063	0.144	0.208	0.179	**0.970**	−0.122	−0.098	0.144	0.035	0.222
ATP2	−0.123	−0.030	−0.186	0.116	0.010	0.176	0.077	0.192	**0.780**	−0.080	−0.001	0.006	−0.036	0.040
ATP3	−0.077	−0.055	−0.047	0.114	0.013	0.139	0.083	0.188	**0.739**	−0.040	0.056	0.065	−0.025	0.030
ATP4	−0.067	−0.015	−0.082	0.124	0.042	0.118	0.116	0.168	**0.733**	−0.011	0.008	0.105	0.014	0.040
AOFA1	−0.019	0.076	0.002	0.139	−0.021	0.205	−0.079	−0.018	−0.026	**0.870**	0.360	0.067	0.134	−0.079
AOFA2	−0.141	0.034	−0.073	0.180	0.022	0.154	−0.071	0.028	−0.072	**0.825**	0.288	0.027	0.096	−0.055
AOFA4	0.105	0.007	0.137	0.084	0.139	−0.033	−0.045	0.003	−0.175	**0.790**	0.234	0.127	0.178	−0.068
FM1	0.214	0.162	0.214	0.002	0.119	0.090	−0.026	0.022	−0.131	0.302	**0.755**	0.058	0.179	−0.043
FM2	−0.001	0.088	−0.001	0.042	0.044	0.133	−0.060	0.067	−0.038	0.340	**0.977**	−0.019	0.222	−0.131
PQI1	0.353	0.228	0.426	0.016	0.185	0.126	0.258	0.238	0.127	0.070	−0.021	**0.900**	0.158	0.427
PQI2	0.278	0.206	0.297	0.015	0.170	0.146	0.292	0.193	0.089	0.092	0.016	**0.823**	0.199	0.315
PQI3	0.290	0.139	0.314	0.009	0.165	0.112	0.219	0.260	0.114	0.080	0.015	**0.858**	0.153	0.280
PC1	0.145	0.327	−0.003	0.208	0.249	0.221	0.133	0.122	0.026	0.124	0.212	0.176	**0.905**	0.094
PC2	0.133	0.180	0.121	0.134	0.230	0.105	0.153	0.153	−0.034	0.176	0.129	0.163	**0.781**	0.077
PC5	0.125	0.360	0.011	0.166	0.252	0.260	0.141	0.172	0.052	0.140	0.244	0.171	**0.909**	0.094
SI1	0.344	0.240	0.399	0.105	0.234	0.191	0.393	0.221	0.187	−0.061	−0.100	0.356	0.101	**0.935**
SI3	0.323	0.206	0.340	0.115	0.273	0.213	0.446	0.306	0.151	−0.056	−0.088	0.417	0.087	**0.936**
SI4	0.332	0.215	0.263	0.075	0.266	0.216	0.436	0.282	0.159	−0.112	−0.141	0.352	0.095	**0.894**

Appendix 3. Discrimant Validity - Cross Loadings (Hedonic)

	PPROF	PSROF	DWF	AC	PR	QV	PV	EV	ATP	AOFA	FM	PQI	PC	SI
PROF1	**0.847**	0.479	0.260	0.069	0.155	0.044	0.121	0.114	−0.011	0.015	0.013	0.386	0.171	0.292
PROF2	**0.896**	0.441	0.353	−0.022	0.180	−0.021	0.159	0.051	−0.089	−0.100	0.011	0.274	0.071	0.332
PROF3	**0.861**	0.504	0.388	−0.069	0.182	−0.005	0.105	0.112	−0.010	0.059	0.123	0.290	0.167	0.314
PROF6	0.548	**0.976**	0.154	0.005	0.185	0.150	0.126	0.098	0.014	0.042	0.110	0.244	0.348	0.264
PROF7	0.363	**0.753**	−0.014	0.140	0.132	0.110	0.107	0.040	−0.018	0.059	0.094	0.105	0.206	0.087
DWF1	0.351	0.131	**0.884**	−0.064	0.093	0.039	0.115	0.086	−0.077	0.057	0.063	0.337	0.051	0.307
DWF2	0.350	0.123	**0.931**	−0.103	0.098	−0.038	0.132	0.070	−0.017	0.022	0.078	0.362	0.019	0.347
DWF4	0.343	0.077	**0.887**	−0.047	0.116	−0.052	0.141	0.074	−0.032	0.011	0.010	0.412	0.051	0.324
AC1	−0.004	0.048	−0.109	**0.924**	0.355	0.244	0.134	0.185	0.095	0.144	0.047	0.012	0.181	0.101
AC2	−0.015	0.029	−0.037	**0.917**	0.349	0.195	0.097	0.168	0.060	0.148	0.016	0.017	0.182	0.096
AC10	0.145	0.222	0.013	0.339	**0.798**	0.114	0.142	0.120	0.030	0.046	0.098	0.137	0.307	0.211
AC8	0.158	0.016	0.145	0.303	**0.771**	0.042	0.211	0.184	0.024	0.025	0.016	0.169	0.118	0.255
AC9	0.170	0.243	0.102	0.259	**0.807**	0.054	0.169	0.168	0.087	0.062	0.055	0.173	0.270	0.184
QV1	0.023	0.108	0.045	0.172	0.082	**0.925**	0.381	0.518	0.171	0.108	0.109	0.170	0.186	0.259
QV2	−0.005	0.171	−0.033	0.281	0.102	**0.874**	0.351	0.486	0.108	0.134	0.141	0.114	0.223	0.160
QV3	−0.017	0.148	−0.123	0.213	0.041	**0.855**	0.409	0.511	0.133	0.124	0.109	0.080	0.225	0.132
PV1	0.140	0.138	0.159	0.094	0.185	0.383	**0.875**	0.412	0.173	−0.089	−0.072	0.258	0.125	0.394
PV2	0.166	0.085	0.125	0.123	0.203	0.408	**0.919**	0.524	0.162	−0.048	−0.011	0.294	0.174	0.453
PV3	0.091	0.139	0.106	0.123	0.217	0.353	**0.910**	0.460	0.179	−0.078	−0.074	0.251	0.138	0.397
EV1	0.150	0.091	0.108	0.122	0.172	0.497	0.506	**0.905**	0.198	−0.043	0.032	0.253	0.100	0.301
EV2	0.036	0.092	0.039	0.205	0.153	0.589	0.459	**0.905**	0.190	0.024	0.060	0.177	0.176	0.225
EV3	0.080	0.061	0.072	0.205	0.216	0.460	0.431	**0.894**	0.152	0.034	0.077	0.280	0.199	0.255
ATP1	−0.015	0.024	−0.007	0.055	0.063	0.144	0.208	0.179	**0.970**	−0.122	−0.098	0.144	0.035	0.222
ATP2	−0.123	−0.030	−0.186	0.116	0.010	0.176	0.077	0.192	**0.780**	−0.080	−0.001	0.006	−0.036	0.040
ATP3	−0.077	−0.055	−0.047	0.114	0.013	0.139	0.083	0.188	**0.739**	−0.040	0.056	0.065	−0.025	0.030
ATP4	−0.067	−0.015	−0.082	0.124	0.042	0.118	0.116	0.168	**0.733**	−0.011	0.008	0.105	0.014	0.040
AOFA1	−0.019	0.076	0.002	0.139	−0.021	0.205	−0.079	−0.018	−0.026	**0.870**	0.360	0.067	0.134	−0.079
AOFA2	−0.141	0.034	−0.073	0.180	0.022	0.154	−0.071	0.028	−0.072	**0.825**	0.288	0.027	0.096	−0.055
AOFA4	0.105	0.007	0.137	0.084	0.139	−0.033	−0.045	0.003	−0.175	**0.790**	0.234	0.127	0.178	−0.068
FM1	0.214	0.162	0.214	0.002	0.119	0.090	−0.026	0.022	−0.131	0.302	**0.755**	0.058	0.179	−0.043
FM2	−0.001	0.088	−0.001	0.042	0.044	0.133	−0.060	0.067	−0.038	0.340	**0.977**	−0.019	0.222	−0.131
PQI1	0.353	0.228	0.426	0.016	0.185	0.126	0.258	0.238	0.127	0.070	−0.021	**0.900**	0.158	0.427
PQI2	0.278	0.206	0.297	0.015	0.170	0.146	0.292	0.193	0.089	0.092	0.016	**0.823**	0.199	0.315
PQI3	0.290	0.139	0.314	0.009	0.165	0.112	0.219	0.260	0.114	0.080	0.015	**0.858**	0.153	0.280
PC1	0.145	0.327	−0.003	0.208	0.249	0.221	0.133	0.122	0.026	0.124	0.212	0.176	**0.905**	0.094
PC2	0.133	0.180	0.121	0.134	0.230	0.105	0.153	0.153	−0.034	0.176	0.129	0.163	**0.781**	0.077
PC5	0.125	0.360	0.011	0.166	0.252	0.260	0.141	0.172	0.052	0.140	0.244	0.171	**0.909**	0.094
SI1	0.344	0.240	0.399	0.105	0.234	0.191	0.393	0.221	0.187	−0.061	−0.100	0.356	0.101	**0.935**
SI3	0.323	0.206	0.340	0.115	0.273	0.213	0.446	0.306	0.151	−0.056	−0.088	0.417	0.087	**0.936**
SI4	0.332	0.215	0.263	0.075	0.266	0.216	0.436	0.282	0.159	−0.112	−0.141	0.352	0.095	**0.894**

Appendix 4. Discrimant Validity - Cross Loadings (Utilitarian)

	PPROF	PSROF	DWF	AC	PR	QV	PV	EV	ATP	AOFA	FM	PQI	PC	SI
PROF1	**0.863**	0.581	0.313	0.069	0.263	0.093	0.288	0.216	−0.203	0.038	0.211	0.532	0.287	0.290
PROF2	**0.885**	0.535	0.353	0.010	0.237	0.050	0.249	0.143	−0.173	−0.089	0.198	0.344	0.131	0.289
PROF3	**0.882**	0.529	0.341	−0.088	0.266	0.067	0.284	0.169	0.025	0.034	0.369	0.320	0.186	0.368
PROF6	0.607	**0.987**	0.177	0.025	0.275	0.344	0.507	0.330	−0.077	0.041	0.268	0.397	0.422	0.330
PROF7	0.544	**0.828**	0.049	0.029	0.121	0.206	0.363	0.275	−0.182	0.080	0.255	0.292	0.217	0.096
DWF1	0.388	0.125	**0.895**	0.038	0.247	0.177	0.307	0.237	−0.128	0.026	0.162	0.312	0.146	0.279
DWF2	0.328	0.138	**0.913**	−0.028	0.157	0.013	0.214	0.147	−0.034	0.051	0.195	0.277	0.142	0.301
DWF4	0.327	0.157	**0.900**	0.083	0.197	0.106	0.271	0.225	−0.032	0.077	0.114	0.373	0.182	0.327
AC1	0.052	0.089	−0.002	**0.922**	0.437	0.162	0.080	0.073	0.262	0.264	0.070	0.094	0.118	0.231
AC2	−0.081	−0.049	0.071	**0.896**	0.423	0.043	0.052	0.083	0.151	0.248	−0.114	0.124	0.168	0.201
AC10	0.260	0.240	0.166	0.475	**0.847**	0.055	0.224	0.075	0.108	0.263	0.142	0.255	0.401	0.453
AC8	0.233	0.127	0.163	0.313	**0.770**	0.079	0.112	0.269	0.092	0.203	0.197	0.271	0.171	0.343
AC9	0.207	0.239	0.214	0.328	**0.803**	0.110	0.321	0.190	0.173	0.276	0.174	0.293	0.290	0.320
QV1	0.021	0.222	0.145	0.084	0.131	**0.926**	0.499	0.539	0.098	0.006	0.245	0.225	0.233	0.326
QV2	0.106	0.383	0.068	0.177	0.060	**0.838**	0.456	0.560	0.003	0.119	0.301	0.223	0.263	0.195
QV3	0.122	0.323	0.037	0.063	0.032	**0.876**	0.490	0.519	0.152	0.103	0.217	0.236	0.256	0.182
PV1	0.293	0.436	0.254	0.068	0.194	0.433	**0.874**	0.372	0.046	0.026	0.198	0.441	0.333	0.330
PV2	0.256	0.402	0.195	0.090	0.242	0.517	**0.911**	0.499	0.078	0.069	0.208	0.485	0.362	0.391
PV3	0.303	0.510	0.332	0.047	0.281	0.523	**0.934**	0.544	0.029	0.116	0.321	0.482	0.352	0.465
EV1	0.201	0.313	0.204	0.044	0.195	0.519	0.505	**0.902**	0.111	−0.013	0.301	0.434	0.197	0.299
EV2	0.140	0.331	0.194	0.116	0.125	0.597	0.449	**0.904**	0.169	0.036	0.254	0.385	0.234	0.273
EV3	0.193	0.245	0.201	0.071	0.234	0.509	0.459	**0.868**	0.063	0.122	0.275	0.414	0.338	0.265
ATP1	−0.099	−0.091	−0.043	0.193	0.159	0.096	0.099	0.101	**0.968**	0.012	0.080	0.130	0.056	0.193
ATP2	−0.205	−0.161	−0.149	0.206	−0.015	0.118	−0.063	0.132	**0.804**	−0.016	0.086	0.003	−0.019	0.040
ATP3	−0.097	−0.088	−0.081	0.288	0.150	0.048	−0.031	0.165	**0.844**	−0.040	0.123	0.066	0.019	0.068
ATP4	−0.143	−0.137	−0.117	0.267	−0.008	0.051	−0.023	0.114	**0.693**	0.008	0.075	0.026	−0.028	−0.011
AOFA1	0.022	0.101	0.014	0.192	0.152	0.136	0.068	0.071	−0.031	**0.876**	0.264	0.064	0.221	0.091
AOFA2	−0.063	0.048	−0.006	0.333	0.308	0.075	0.046	0.043	0.050	**0.937**	0.203	0.027	0.115	0.187
AOFA4	0.103	−0.017	0.206	0.109	0.289	−0.048	0.131	0.019	−0.089	**0.700**	0.213	0.186	0.113	0.089
FM1	0.351	0.272	0.187	−0.034	0.207	0.295	0.296	0.268	0.062	0.210	**0.964**	0.187	0.199	0.247
FM2	0.083	0.198	0.075	0.032	0.134	0.160	0.122	0.312	0.156	0.281	**0.737**	0.093	0.212	0.097
PQI1	0.421	0.364	0.399	0.114	0.284	0.260	0.463	0.367	0.151	0.059	0.212	**0.888**	0.344	0.553
PQI2	0.374	0.354	0.233	0.117	0.303	0.137	0.435	0.359	0.017	0.101	0.102	**0.818**	0.391	0.378
PQI3	0.368	0.309	0.272	0.079	0.292	0.252	0.457	0.486	0.094	0.074	0.133	**0.904**	0.357	0.452
PC1	0.237	0.332	0.146	0.150	0.298	0.265	0.389	0.157	0.036	0.082	0.170	0.358	**0.897**	0.375
PC2	0.132	0.263	0.164	0.123	0.345	0.108	0.287	0.245	−0.012	0.139	0.117	0.315	**0.803**	0.326
PC5	0.219	0.426	0.150	0.133	0.325	0.333	0.328	0.336	0.080	0.200	0.286	0.402	**0.911**	0.401
SI1	0.344	0.276	0.378	0.261	0.388	0.217	0.395	0.256	0.155	0.163	0.177	0.484	0.362	**0.926**
SI3	0.319	0.275	0.298	0.232	0.498	0.276	0.479	0.345	0.168	0.165	0.231	0.551	0.463	**0.942**
SI4	0.346	0.253	0.249	0.159	0.399	0.292	0.333	0.254	0.120	0.113	0.217	0.444	0.328	**0.885**