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From Fitness Tracking to Augmented Shopping Experience: Perceptions and Use of Mobile Payment among Runners Using Wearable Devices

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Abstract

Regularly exercising users of sports wearables (e.g., smartwatches) comprise an overlooked group in the literature on mobile payment despite their frequent use of such high-tech devices that allow making mobile payments. Payment-capable wearables could lead to a more health-conscious shopping experience through push notifications that make customised suggestions—say, for fluid/food intake based on dehydration/calories burnt, since they track exercise (e.g., steps), health (e.g., pulse), and well-being data (e.g., sleep cycles). Accordingly, this study aims to explore the perceptions and use of mobile payment technology among a sample of runners, who track their exercise metrics using sports wearables. A typical runner that we captured data from was an educated, employed, and adult female user of high-tech sports wearables, who makes nearly 9 kilometres on each of her four runs in a week, but taps her smartphone—not her wearable—to make payments for necessity goods (e.g., food, apparel) and services (e.g., bills, bookings) through either Alipay or Apple Pay. Mobile payment was among the top three preferred methods of payments; however, only 4% were using their wearable device for that purpose. Runners had a positive perception of the mobile payment technology, which was homogeneous across the categories of their socio-demographic characteristics and exercise metrics. These results indicate that mobile payment use on a smartphone is common among the physically active, but the convergence of that technology with high-tech wearable devices is yet to find acceptance.

Keywords: High-tech sports wearables, Health-conscious shopping, Mobile payment, Perceptions and use, Runners

INTRODUCTION

High-tech sports wearables (e.g., GPS-enabled fitness bracelets) help motivate physically active users to exercise more and effectively by providing them with, for instance, real-time metrics (e.g., interval-based workouts, pace by splits) comparable to past performances or the performances of others on their social fitness circles (e.g., Fitbit Community, clubs on Strava). The pioneers of the latest generation of wearables converge smartphone technology into wearable devices so that they can run software applications (also known as 'apps') within networks over the Internet. Among that software are payment apps (e.g., Google Pay) that enable users to make purchases with their wearables, such as Suunto—the Finnish smartwatch brand, and Glass—Google's smart spectacles.

Unlike hand-held smartphones, users fasten wearables to their bodies to observe a range of health and wellbeing data such as sleep/stress patterns, and physical (e.g., exercise intensity), physiological (e.g., heart rate) and chemical performance (e.g., calories burnt). Aside from allowing safer multitasking on the go (e.g., as Google Glass does), the new generation of wearables could increase mobile payment use among not just exercising but also recreationally active users by providing them with customised purchase suggestions based on their health and wellbeing data as traced by their smart devices (1). However, smartphone-user biasing or sedentary samples in earlier works on the perceptions and use of mobile payment have overlooked the exercising users of sports wearables.

The consumer line of the relevant literature provides insights into two main domains. One that focuses on people's adoption of mobile payment technology has unearthed that the more the positive users' emotions about mobile payment are, the higher (lower) the technology's perceived usefulness (risk) gets (2). Perceived usefulness stimulates people's intention to use mobile payment services (3, 4) through attitude formation (5). Perceived risk [e.g., of system security and privacy issues (6–8)], on the other hand, reportedly exerts a negative influence on the adoption of mobile payment technology (9). The second domain has revealed the frequently purchased items through mobile payment, which mainly comprise clothing and footwear (10), food, tickets and parking (11), bill/invoice payments (12), hotel bookings (13), and public transportation services (14–16).

Whether these findings from studies that mainly employ samples pursuing sedentary-abiding lifestyles hold for exercising individuals notwithstanding, research on mobile payment among the users of sports wearables has been sparse. The next generation of sports wearables that enable mobile payment provides not just an augmented shopping experience for exercising individuals based on their quantified selves [(17) e.g., push notifications about suggestions for the replacement of fluids lost through sweat when exercising] but also an opportunity for the socially responsible businesses to personalise their customer relationship management towards building a more health-consciousness society. Accordingly, we surveyed a sample of runners using fitness wearables for their current perceptions and future intentions related to using mobile payment.

Next, we provide the methodological details of our study. Then, we report our test results. A discussion on the findings and contemplations of their possible implications conclude the paper.

MATERIAL AND METHOD

Design and Procedures

We invited the members of a New Zealand-based running club on a social fitness network to participate in our descriptive study in mid-2019. A link in our recruitment post took volunteers to the welcoming page of the online survey that we created in Google Forms. The landing page explained subjects about the research and its terms. A click to proceed with the survey questions obtained participants' informed consents. Before data analysis, we excluded 75 submissions that contained missing values. We also checked for extremities that fall outside the 95% confidence interval by converting the scores on the 20-item device (see 'instrument') into z scores and excluded 12 such cases. We computed the average variance expected (AVE), composite reliability (CR), and Cronbach's alpha values [following the same procedures explained in Zhou (18)] for a comparison of the inter-item reliability of each dimension.

Table 1. Comparison of the present and benchmark[a] studies by standardised item loadings, AVE, CR, and Cronbach's α[b]

		Standardised loadings		AVE (CR)		Cronbach's α	
Factor	*Item*	*Present*	*Benchmark*	*Present*	*Benchmark*	*Present*	*Benchmark*
Trust in mobile payment (TMP)	TMP1	.749	.869	.626 (.833)	.65 (.85)	.751	.84
	TMP2	.743	.848				
	TMP3	.874	.692				
System quality (SYS)	SYS1	.675	.744	.635 (.874)	.51 (.81)	.878	.80
	SYS2	.837	.667				
	SYS3	.785	.746				
	SYS4	.877	.704				
Information quality (INF)	INF1	.922	.826	.696 (.900)	.62 (.83)	.904	.82
	INF2	.853	—[c]				
	INF3	.856	.877				
	INF4	.687	.650				
Performance expectancy (PE)	PE1	.662	.867	.590 (.810)	.62 (.83)	.735	.82
	PE2	.767	.771				
	PE3	.862	.713				
Flow (FLOW)	FLOW1	.771	.654	.544 (.774)	.55 (.79)	.682	.78
	FLOW2	.874	.783				
	FLOW3	.522	.789				
Usage continuance (USE)	USE1	.530	.765	.302 (.560)[d]	.60 (.82)	.524[d]	.81
	USE2	.651	.691				
	USE3	.450	.862				

Notes: Sample size in present (benchmark) study = 336 (226). See benchmark study for item statements. Measurement on 5-point scale. [a]Zhou (18). [b]The benchmark study reports factor loadings in three decimal points and AVE, CR, and alpha figures in two decimal points. [c]The benchmark study drops item INF2 due to its high correlation with the error variances of other items [see p. 942 in Zhou (18)]. [d]We interpreted the weak effect that AVE = .302 indicates as sufficient validity within the context of its square root, which is higher than all factor correlation coefficients (see Table 2). This interpretation is in line with Borsboom, Mellenbergh, and Van Heerden's ontological approach in their 2004 paper entitled "The concept of validity" published in Psychological Review, 111(4):1061-107. We followed the guidelines Field (19, p. 675) provides for interpreting alpha and considered α = .524 as reliable in context as the average correlation between the items comprising the USE dimension was a respectable .48.
Abbreviations: AVE = average variance extracted, CR = composite reliability

Sample

Four-hundred and twenty-three (of 617) volunteering runners passed through the filter (see 'instrument'), 194 (31%) of them did not fit for what we want to study for using either no device or a non-high-tech wearable (e.g., regular watch) or a smartphone while exercising. After the afore-mentioned exclusions remained 336 runners in the sample (55% female). Subjects were running 2 ≤ M = 3.8 (SD = 1.1) ≤ 6 times a week and travelling 2 ≤ M = 8.7 (SD = 5.7) ≤ 31.8 kilometres per run. These figures were homogeneous among gender groups: t (334) runs/week = .486, p = .314 and t (334) km/run = –.285, p = .338. By age, three-quarters were in their 30s [38%, running M (SD) = 4.8 (.87) times/week, travelling 6.8 (5.3) km/run] and 40s [37%, running M (SD) = 3.5 (.56) times/week, travelling 9.2 (5.4) km/run]. The remainder were either in their 50s [19%, running M (SD) = 2.6 (.63) times/week, travelling 12.8 (5.3) km/run,] or 20s [6%, running M (SD) = 2.9 (.88) times/week, travelling 5.51 (2.37) km/run; F (3, 332) runs/week = 146.753, and F (3, 332) km/run = 21.565, ps < .001]. The runners in the sample were educated (73% had a degree, 19% post-degree, 8% pre-degree). More than four-fifths were economically active (i.e., 68% employed plus 15% self-employed), the rest were either students (8%) or unemployed (1%; 8% did not prefer to answer).

Instrument

A filter question distinguished fitness wearable users from non-users. Then, a self-administered quadripartite questionnaire asked each participating runner a set of 31 questions. The opener contained six descriptive items (reported in 'sample'). The two scaled items in the second section asked about frequently used payment methods (1 = hardly ever, 5 = almost always) and the extent to which each payment method was found frustrating due to security, difficulty or complexity (1 = not frustrating at all, 5 = very much frustrating). The third part had three structured questions exploring mobile payment use (i.e., items purchased, non-bank app/s used, and choice of payment). The 20-item 5-point scale in the last section that we adapted from Zhou (18) determined the runners' perceptions of and intentions to continue using mobile payment technology (1 = strongly disagree, 5 = strongly agree).

Validity Checks

The sample size was sufficiently large (orthogonal rotation, KMO = .967, Bartlett's p < .001) and allowed us to compare the factorial structure of the 20-item device that conceptualises the mobile payment usage to Zhou (18)—the source we benchmarked. Prelim to data analysis, six components emerged after seven iterations, explaining together 84% of the total variance. The structure was similar to Zhou (18)'s; therefore, we named the components identically as the source (see table 1). The emerged factors were statistically heterogeneous, indicating that the 6-factor structure also had good discriminant validity (20, p. 1525). We replicated Zhou (18)'s procedures for discriminant validity and compared the square root of AVE values to the factor correlation coefficients. For each factor, the square root of AVE was higher than the factor correlation coefficients; thus, confirming validity (see table 2).

Table 2. Comparison of factor correlation coefficients and the square root of AVE values for discriminant validity

Factors	*1*	*2*	*3*	*4*	*5*	*6*
1. TMP	***.7910***					
2. SYS	.6084	***.7971***				
3. INF	.5005	.6109	***.8340***			
4. PE	.5200	.6704	.6440	***.7680***		
5. FLOW	.5279	.6034	.5591	.6246	***.7373***	
6. USE	.4554	.5166	.3903	.5197	.5146	***.5499***

Notes: The square root of AVE is shown in bold italics at diagonal. Sample size (n) = 336.
Abbreviations: AVE = average variance extracted, TMP = trust in mobile payment, SYS = system quality, INF = information quality, PE = performance expectance, FLOW = flow, USE = usage continuance. Scores on 5-point scale (1 = strongly disagree)

RESULTS

Runners' Choice of Payment Method

All subjects were making mobile payments when shopping; however, only a minority (4%) stated using their fitness wearable for that purpose (96% using either a bank or non-bank payment app on smartphone). Figure 1 depicts the rank comparisons of the often preferred and the most frustrating ways of making payments. Mobile payment ($M = 3.49$, $SD = 1.00$) was among the three methods that runners frequently prefer, although ranked significantly behind the in-store EFTpos ($M = 3.96$, $SD = 1.49$) and debit card use [$M = 3.80$, $SD = 1.54$, $F\ (2, 1005) = 10.189$, $p < .001$]. Conversely, ranking was homogenous among store cards ($M = 1.92$, $SD = 1.31$), Paypal ($M = 1.98$, $SD = 1.16$), and cheques [$M = 2.01$, $SD = 1.48$, $F\ (2, 1005) = .434$, $p = .648$], which were the three payment methods used the least.

Paired comparisons revealed that frustration data were mostly in line with the frequency data. Runners, for instance, reported the least frustration in using EFTpos [$M = 1.95$, $SD = .91$, $t\ (335) = 21.072$, $p < .001$] and debit card payments in store [$M = 1.76$, $SD = .85$, $t\ (335) = 20.803$, $p < .001$]. Mobile data ranked relatively high on the frustration scale ($M = 2.96$, $SD = 1.27$), but its frequent use seemed to outscore the feeling of frustration [$t\ (335) = 6.243$, $p < .001$]. Findings indicated that online payments by credit ($M = 4.01$, $SD = .92$) and debit cards ($M = 3.77$, $SD = 1.03$) and through phone banking ($M = 3.38$, $SD = 1.10$) result in higher levels of frustration among other methods. A worthwhile finding to note is that online credit card and EFTpos use were both ranked in the top-five for not just the most frequently preferred payment methods (Ms = 3.22 and 3.20, SDs = 1.72 and 1.44, all respectively) but also the most frustrating (M EFTpos = 2.96, $SD = 1.27$). By frequency of use the two were indifferent [$t\ (670) = -.219$, $p = .413$], however, the runners found online payments by credit cards more frustrating [$t\ (670) = -11.356$, $p < .001$].

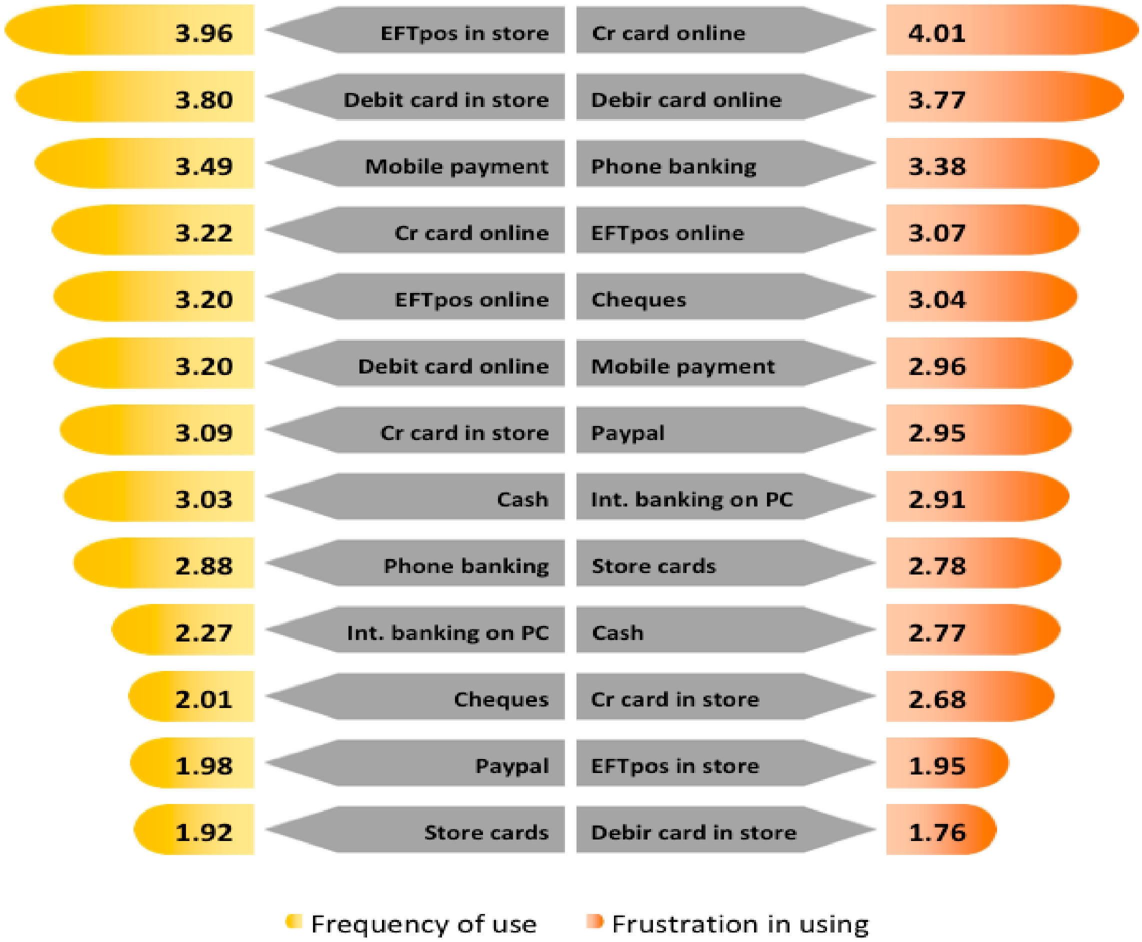

Figure 1. Runners' choice: Frequently used (left) vs the most frustrated payment methods

Notes: Sample size (n) = 336. Mean scores on 5-point scale, higher scores indicate higher levels of frequency and frustration.

Runners' Mobile Payment Use

Figure 2 illustrates the frequency distribution of the items (by category) that subjects purchase using mobile payment regularly. Nearly two-thirds of mobile payments were for two product categories. Necessity goods (i.e., food, clothing/footwear) were the top purchase item, constituting one-third of runners' mobile spending. Making up nearly 30%, service purchases (i.e., bills, tickets, bookings) followed that. The remaining 40% was evenly allocated across the three groups of items: household goods (i.e., appliances, furniture, DIY/home improvement, 14%), electronics and entertainment goods (13%), and health/beauty and adornments (13%).

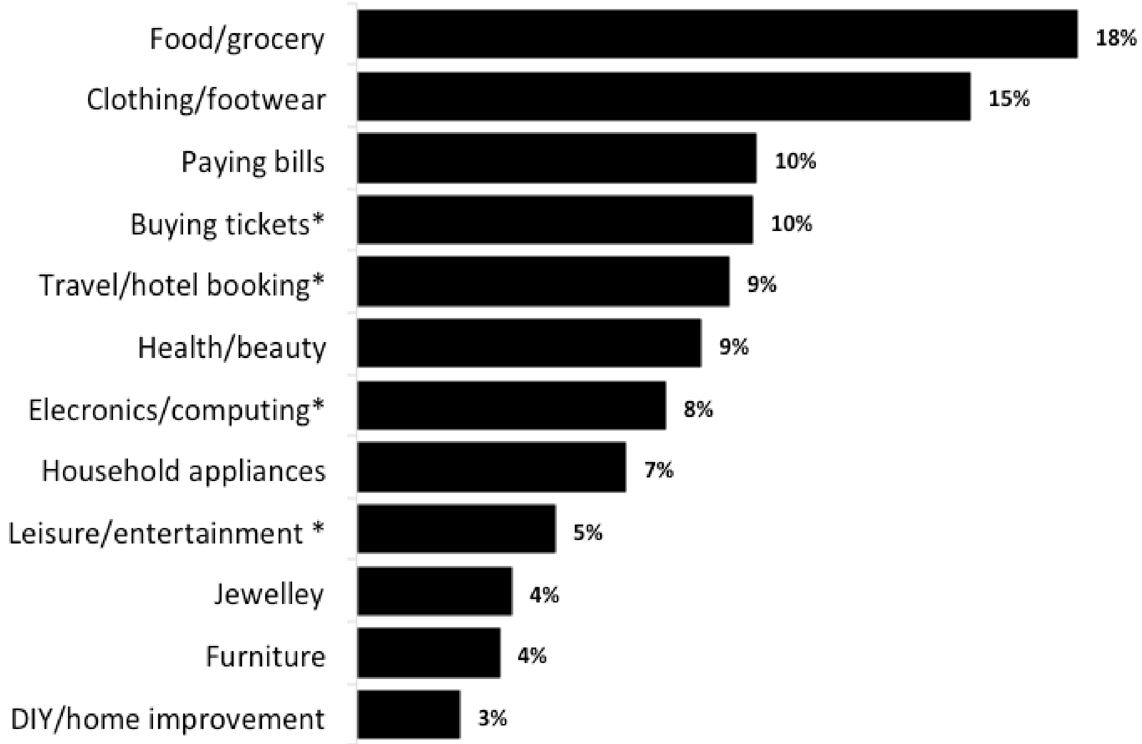

Figure 2. Items runners frequently purchased using mobile payment

Notes: Sample size (n) = 336. The % total is different from 100 due to rounding. DIY = do it yourself.

*Tickets include concert, movie, theatre, sport games, and public transportation. Tickets for flights and other travel arrangements are included in travel/hotel booking. The electronics/computing group captures phones, tech devices, and their accessories (e.g., ear plugs). Leisure/entertainment includes books, music, videos, and computer games.

Subjects stated six different non-bank apps that they were using for making mobile payments (see fig. 3). Alipay and Apple Pay were the two most used among them, preferred by slightly less than three-quarters in the sample. Almost a third of the runners stated their interest in using WeChat Pay, the only other Chinese mobile payment app among responses. Apple Pay seconded that (31%). It was typical across the sample that Android-based mobile payment systems (i.e., Samsung Pay and Android Pay) were not known, thus used by only a minority. Tap-to-pay was the choice of 75% while only a quarter was using the scan-to-pay way of making a mobile payment.

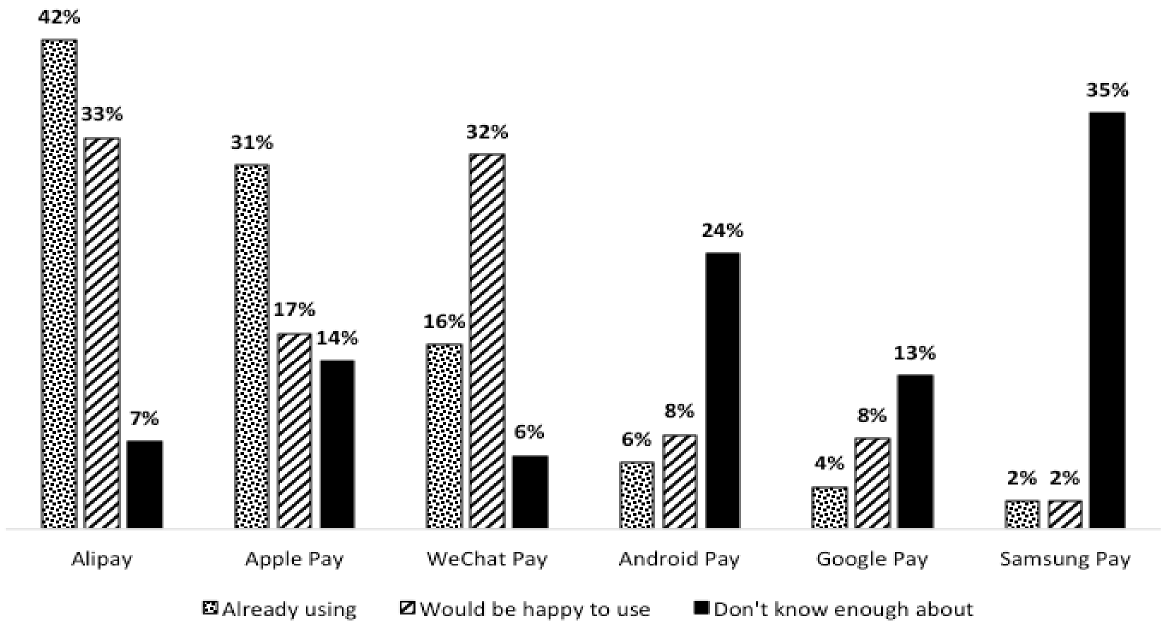

Figure 3. Non-bank apps that runners use for making mobile payment

Notes: Sample size (n) = 336. The % total is different from 100 in 'Already using' and 'Don't know enough about' responses due to rounding.

The current mobile payment usage was significantly correlated with all dimensions of the construct (see table 3). The relatively stronger correlations indicated that perceived information (INF) and system qualities (SYS), performance (PE) and trust (TMP) components could predict the runners' current mobile payment usage better than flow and usage continuance (USE).

The mobile payment usage was homogenous across the runners with respect to their sociodemographic characteristics: gender [t (334) = .235, p = .407], age [F (3, 332) = 1.454, p = .227], education level [F (2, 333) = 1.936, p = .146], and employment status [t (308) = –.693, p = .244]. The last of these foursome of analyses excluded the 8% who preferred to retain their employment information, and compared the economically active (i.e., employed and self-employed) to economically inactive runners (i.e., studying and not working). Similarly, the runners' mobile payment use did not differ by their physical activity levels as measured by the number of weekly runs [F (4, 331) = .403, p = .807]. Neither the times per week a runner was active [R = .016, F (1, 334) = .085, p = .771] nor the distance they travel per run [R = .022, F (1, 334) = .165, p = .685] predicted mobile payment use.

Table 3. Correlations between the usage frequency of mobile payment and the dimensions of the six-factor structure

Factors	*1*	*2*	*3*	*4*	*5*	*6*
1. TMP	—					
2. SYS	.6084	—				
3. INF	.5005	.6109	—			
4. PE	.5200	.6704	.6440	—		
5. FLOW	.5279	.6034	.5591	.6246	—	
6. USE	.4554	.5166	.3903	.5197	.5146	—
7. MP usage frequency	.3657	.4474	.4582	.4095	.2766	.1426

Notes: Correlations are significant at $p \leq .008$. Sample size (n) = 336. Dependent variable (Y) = MP usage frequency, multiple independent (predictor) variables (Xs) = the six factors. $R = .5391$, $R^2 = .2906$, F (6, 329) = 22.461, $p < .001$

Abbreviations: TMP = trust in mobile payment, SYS = system quality, INF = information quality, PE = performance expectance, FLOW = flow, USE = usage continuance, MP = mobile payment. Scores on 5-point scale (1 = strongly disagree)

DISCUSSION AND CONCLUSION

We attempted to determine the perceptions and use of mobile payment among a sample of New Zealand-based runners using sports wearables (e.g., smartwatches), which appears in the relevant literature as an overlooked group despite their use of high-tech devices that allow making mobile payments. Our online instrument adopted a 20-item device developed to measure the perceptions and use of mobile payment technology.

A typical runner in the sample was an educated, employed, and adult female user of high-tech sports wearables, who makes nearly 9 kilometres on each of her four runs in a week, but taps her smartphone—not her wearable—to make payments for necessity goods (e.g., food, apparel) and services (e.g., bills, bookings) through either Alipay or Apple Pay. When the items purchased through mobile payment are considered, these findings seemed in line with those of other studies employing smartphone-using sedentary samples (10–13). Similarly, a majority in our sample was younger than 40 years of age, which conformed to the user typification by age that most studies report (e.g., 21, 22). Mobile payment usage was uniform between the categories of both the demographics and exercise metrics of the sampled runners. These results partly echoed the findings from studies with sedentary samples indicating more extensive use among young adults (23, 24) and homogeneity across gender groups (21, 22); however, conflicted few that report otherwise (25). Overall, the unvarying use of the technology among their statistical characteristics and running metrics indicates exercising groups could provide health-conscious samples that are as resourceful as those comprising people of sedentary lifestyles for studies that converge mobile shopping with health and wellbeing tracking.

Findings from the predictive analysis were somewhat monolithic in the runners' present and future evaluations of mobile payments. The frequency of a runner's mobile payment use at present (i.e., MP usage frequency) correlated strongly with their perceived information and system qualities of, the service performance of, and trust in the technology, as well as flow and future use (i.e., USE). Except for service performance and trust (26–28), our observations on system quality, information quality, and flow were in disagreement with earlier studies (5, 18, 29, 30). These results suggest that service performance and trust elements of mobile payment technology, as perceived by users, are universal among the sedentary and physically active samples whereas their perceptions of other factors indicative of mobile payment use distinguish the latter group. However, only a negligible 4% in our sample were using their wearable device for making payments; smartphone was their dominant payment-making device. When the fact that the use of mobile payment technology on a smartphone has become common is considered, our finding indicates that the convergence of that technology with a new device—that is, using high-tech sports wearables for making payments—seems to be in its early adoption stage. Therefore, similar studies in the future that will capture data from early or late majority could provide more insight into the perception and use of mobile payment and shopping on high-tech wearable devices.

Its limited geographical reach and selective activity-focus might have thwarted our study. Although a broader reach on the social fitness network, where we recruited our sample, was possible by the inclusion of groups throughout the world, this could have required longer time for data collection. We aimed to complete the study before the start of the festive season in December to optimise returns. Similarly, the findings from our analyses provide only a limited representation of the physically active users of high-tech sports wearables (i.e., runners) who make payments with their mobile devices. Involvers of a spectrum of outdoor sports (e.g., cycling, sailing, and walking) and indoor exercises (e.g., aerobic fitness programmes featuring movements to dance music) could have added more value to the utility of present findings. These limitations could be avenues for future research. It could also be interesting to compare sedentary versus physically active samples at different geographies for their utilisation of high-tech wearable devices in health-conscious purchases based on push notifications reminding them of their physical and physiological metrics.

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