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Predicting the Adoption of Health Wearables with an Emphasis on the Perceived Ethics of Biometric Data

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ABSTRACT

The main purpose of this research is to understand the strongest predictors of wearable adoption among athletes with an emphasis on the perceived ethics of biometric data. We performed a word co-occurrence study of biometrics research to determine the ethical constructs of biometric data. A questionnaire incorporating the Unified Theory of Acceptance and Use of Technology (UTAUT), Health Belief Model and Biometric Data Ethics was then designed to develop a neural network model to predict the adoption of wearable sensors among athletes. Our model shows that wearable adoption's strongest predictors are perceived ethics, perceived profit, and perceived threat; which can be categorized as professional stressors. The key theoretical contribution of this paper is to extend the literature on UTAUT by developing a predictive modeling of factors affecting acceptance of wearables by athletes, and highlighting the ethical implications of athlete's adoption of wearables.

Keywords: Health Wearables, Adoption, Neural Network Analysis, Bibliometric Analysis, Data Ethics

Ⅰ. Introduction

In addition to the growing trend towards enterprise-led remote monitoring projects, many sports teams have been inclined to use the biometric data of their athletes' personal wearables to monitor the health status of team members in real time or to share biometric data, such as cardiac data of athletes in an online social context (Curmi et al., 2017).With the prevalence of inexpensive and personal IoT based health wearables, the emergence of physiological informatics, and predictive analytics (Bai et al., 2017; Curtis et al., 2008; Gaura et al., 2013; Saheb, 2018; Saheb and Izadi, 2019; Saheb and Saheb, 2019), the sport industry can extract many actionable insights from collection and analysis of wearable biometric

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data. Although it is claimed that data on wearables will be used to modify training, a new wave of ethical concerns has also emerged (Arnold and Sade, 2017). Increased surveillance of players, associated risks in terms of data security and privacy (Karkazis and Fishman, 2017); and threats to professional life of athletes have spread a cloud of ethical concerns over the incorporation of biometric data on personal wearables in the assessment of performance, strengths, weaknesses and talent (Banerjee et al., 2017). Data privacy, security and confidentiality can act as obstacles to the adoption of healthcare IT (Kingsford et al., 2017; Meghani and Geetha, 2016; Rivero-García et al., 2017; Thilakanathan et al., 2014). Many IT users face the dilemma of introducing new technologies that may interfere with their privacy and security(Mnjama et al., 2017) as a result of disclosure of information (Lee et al., 2016), cyber security threats (Grispos et al., 2017; Luna et al., 2016; Mnjama et al., 2017) or information quality (Saheb, 2020).

In an athlete's life, the physiological data of their personal gadgets may be at odds with their professional life. Some scholars have addressed the legality of the biometric screening of professional athletes (Karkazis and Fishman, 2017; Roberts et al., 2017) which This raises' risks of abuse, intimidation and prejudice of employees (Karkazis and Fishman, 2017). For example, in 2015, the NFL Players Association objected to the use of sleep-monitoring technology; however, NFL replied that this procedure took place with the specific consent of the player (Cummins, 2017). Another example is the continuous biometric monitoring of two National Basketball Association players over two seasons using a Whoop device designed to monitor athlete's heart rate, skin temperature, and other health metrics (Haberstroh, 2017). Major League Baseball has allowed the use of this product, but stated that teams can not compel their players to wear this wearable device (Rovell, 2017).

As illustrated on <Table 1>, acceptance of wearables is a growing scholarly trend (e.g., Blumenthal et al., 2018; Chang et al., 2016; Dehghani et al., 2018; Fensli et al., 2008; Guest et al., 2018; Kim and Chiu, 2018; Pfeiffer et al., 2016; Sergueeva and Shaw, 2016; Talukder et al., 2018; Yang et al., 2016). Contrary to this trend, the adoption of wearable sensors by professional athletes with an emphasis on ethical data protection, data security and disclosure of information is highly marginalized in the literature. Moreover, the majority of adoption research on wearable devices discussed only one general dimension of data ethics; that is, privacy (Chang et al., 2016; Spagnolli et al., 2014). The literature lacks an analysis of the other dimensions of data ethics; such as data security and hacking, or disclosure and confidentiality of information. In this study, we attempted to fill this gap by exploring the major dimensions of biometric data ethics.

On the other hand, most studies on the acceptance of wearable technologies have employed a causal-explanatory statistical approach, such as structural equation modeling or partial least square in their research model testing (<Table 1>). Neural network modeling is a very powerful technique in identifying the strongest and weakest predictors of an individual's intention to use a technology. Predictive analytics, such as neural network modeling, is less commonly used in healthcare technology adoption studies. In addition, few studies have applied predictive modeling methods and neural network modeling in order to understand the adoption of technology (Al-Shihi et al., 2018; Chong, 2013; Leong et al., 2013; Tan et al., 2014; Chong et al., 2015). The incorporation of neural network modeling into information system research is important, because it not only leads to the development of technically useful models, but

<Table 1> Some of Relevant Literature on Adoption of Wearable Devices

Study	Technology	Analysis Method	Main Models	Subjects	Perceived Ethics of Data Disclosure, Data Privacy & Data Security
Song et al. (2018)	Smart Connected Sports Products	Partial Least Squares	Theory of Planned Behavior	Product Users	No
Pfeiffer et al. (2016)	Wearable self-tracking technology	Structural Equation Modeling	TAM	Potential users	No
Yang et al. (2016)	Wearable devices	Partial Least Squares (PLS)	TAM	General Customers	No
Chang et al. (2016)	Wearable devices	PLS	TAM TTF (Task Technology Fit)	General users	Only Privacy
Fensli et al. (2008)	Wearable biomedical sensor	Statistical Analysis	TAM UTAUT	Patients	No
Sergueeva and Shaw (2016)	Wristbands in hospitals for recording patient's details ad tracking location	Qualitative	UTAUT PMT (Protection Motivation Theory)	Patients	Only Privacy
Dehghani et al. (2018)	Smart Watch	PLS	TAM	Smart watch users	No
Spagnolli et al. (2014)	Wearable device for psychological parameters	Principal Component Analysis with Orthogonal Rotation	TAM UTAUT	Various social groups such as volleyball players	Only Privacy
Blumenthal et al. (2018)	Wearable device	Factor Analysis and PLS	TAM	Physiologists	No
Guest et al. (2018)	Wearable device	Structural Equation Modeling	UTAUT 2	Professionals	No
Talukder et al. (2018)	Fitness Wearable Technology (FWT)	PLS	UTAUT2 Diffusion of Innovation	General users	No
Kim and Chiu, (2018)	Sport wearable	PLS Structural Equation Modelling	TRAM (Technology acceptance & readiness)	General users	No
Lunney et al. (2016)	Wearable Fitness Technologies (WFT)	Structural Equation Model	TAM	General users	No

also plays an important role alongside explanatory modeling in theoretical building and testing (Shmueli and Koppius, 2011). Unlike conventional statistical techniques that test only linear relationships among variables, the neural network modeling was used in this study to uncover the non-linear relationships and find the most important predictors. The main motivation behind this research is, therefore, to fill out this shortcoming by predicting individuals' influential variables affecting the intention of professional athletes in using fitness wearables. So in comparison of using usual regression methods, we have incorporated neural network analysis as a more accurate predictive method.

<Table 1> summarizes the previous study on wearable adoption, and this study's difference with prior research. First, the sport industry can face challenges with regard to the athletes' intention to use wearables for their continuous monitoring. This study assists the sport industry in identifying factors that affect acceptance of this technology among athletes with a specific emphasis on biometric data ethics. Second, this study's research model and its method of analysis is distinctive from previous studies exploring the adoption of wearable technology. This research is multi-disciplinary (i.e., Sport Management, Management Information Systems, Health Informatics, and Ethics of Data), and our analysis method is based on a machine learning method; called neural network analysis. In this research, we incorporated the Unified Theory of Acceptance and Use of Technology (UTAUT), the Health Belief Model, and the concerns over the ethics of data. Previous research on wearable fitness adoption marginalized the influence of perceived ethics, with its various dimensions, as one of the constructs affecting technology acceptance. This research therefore aims at understanding and predicting the acceptance of wearable sensors in the context of the sport industry by introducing the indicator of perceived ethics to the UTAUT and HBM models. Third, this research will employ neural network analysis to predict the adoption of wearable sensors. Previous studies suggest that no optimized TAM version has been developed for use in health services, there are still areas that can be extended and enhanced to boost the TAM's predictive performance (Rahimi et al., 2018). Neural network analysis has a greater predictive ability compared with previous statistical explanatory methods (Shmueli and Koppius, 2011). Neural network analysis provides advantages, such as less formal statistical training, the ability to detect implicitly complex nonlinear relationships between dependent and independent variables, the ability to detect all possible interactions between predictor variables and the availability of multiple training algorithms (Tu, 1996). The last theoretical contribution of this work is that it seeks to expand the previous studies on acceptance of wearable technology by focusing on professional athletes as technology consumers. Athletes as consumers of the technology play a significant role in the success or failure of real-monitoring projects. Extending the boundaries of real-time tracking into athletes' personal lives poses new questions about athletes' security and privacy; thus, it is critical for decision-makers to consider factors affecting professional athletes' adoption of wearable sensors.

1.1. Ethics of Biometric Data

Ethical discussion of technology has given rise to other concepts of ethics such as responsibility, and risk that were not as common in pre-modern moral philosophy (Mitcham, 1994). Ethics of technology has been a scholarly concern since 1961, as an interdisciplinary research; and is concerned in the ethical aspects of technological systems. However, a new code of ethics is required for big data, because it is distinct from computer ethics and other more general ethical frameworks (O'Leary, 2016). It is important to investigate the ethical implications of biomedical big data, due to the inherent sensitivity of medical information(Mittelstadt and Floridi, 2016). In the field of public health, big data raises issues about data integrity; informed consent; security of privacy, confidentiality and risk, identification of data and reporting of incorrect inferences (Salerno et al., 2017). In the biomedical sector, the areas of concern include informed consent, privacy, ownership, epistemology and the big data divide (Mittelstadt and Floridi, 2016).

One of the main aspects of techno-ethics is the degree in which technology expands or decreases the control of individuals by revealing their private biometric data. Article 4 of the EU General Data Protection Regulation (GDPR) defines biometric data as "personal data resulting from specific technical processing relating to the physical, physiological or behavioral characteristics of a natural person, which allow or confirm the unique identification of that natural person, such as facial images or dactyloscopic (fingerprint) data"(GDPR, 2018). Wearable manufacturers are advised to take the appropriate steps to protect the privacy of their consumers in order to prevent breaches. (Rocha and Guarda, 2018). In their study of ethics of biometric technologies among US professional athletes, Karkaziz and Fishman (2017) identify five areas of concern that are mainly related to data: (1) validity and interpretation of data; (2) increased surveillance and threats to privacy; (3) risks to confidentiality and concerns regarding data security; (4) conflicts of interest; and (5) coercion (Karkazis and Fishman, 2017).

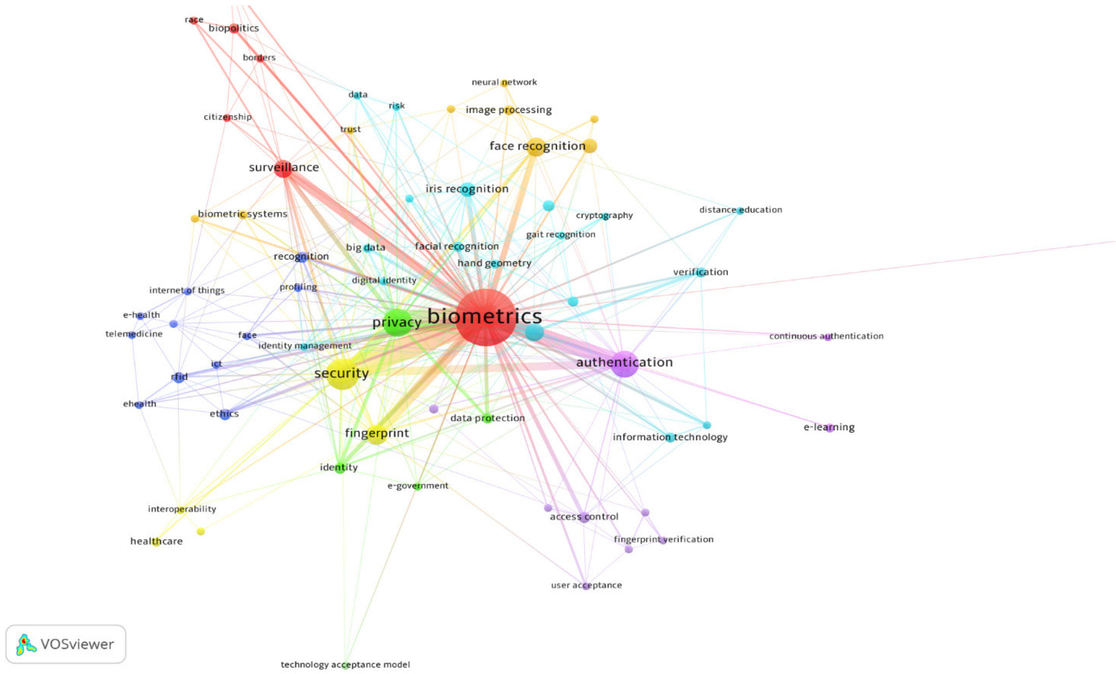
In another study, Osborne and Cunnigham (2017) highlight the legal and ethical implications of athletes' biometric data collection in professional sport. They note that there is no federal law expressly governing the processing of biometric data; and biometric data is not commonly classified as personal health information under the current federal framework (Osborne and Cunningham, 2017). They note that teams are currently self-regulating the extent of security of player data and the degree of consent to the use and release of the data.

One of the ethical problems of biometric data is the ownership of data. The key question is who owns the data?: whether (1) an athlete whose data is being collected; (2) or an institution or entity wishing to use the data, usually a school or professional organization; (3) or a vendor offering biometric equipment and incident services (Lam, 2018). The rise of performance analysis, which has empowered by the biometric data of wearables, has given rise to a number of concerns for both athletes and sporting systems. As <Table 2> shows, questions of consent, confidentiality and ownership are raised for an athlete, while performance analysis increases performance and value for an athlete (Evans et al., 2017).

To better understand the scientific trends in biometric data ethics, we conducted a bibliometric analysis of the term "biometric technology" in the Scopus database on 29 October by searching this term in the keywords, titles and abstracts section. Bibliometric analysis is used for temporal evolution of scientific and invention productivity (Saheb and Saheb, 2020). We included all areas of research; and around 6,127 articles were indexed to the database. We used the VosViewer software for the co-occurrence analysis

<Table 2> Benefits and disbenefits of performance analysis for the athlete and sporting system (Evans et al., 2017)

Benefits for the athlete	Benefits for the system	Disbenefits for the athlete	Disbenefits for the system
Increased performance data	Improved safety in sport	Athlete consent, confidentiality and data ownership	Unfair competition in sport-'technology doping'
Increased value for the athlete	Deterrence to cheating	De-skilling of an athlete	Can facilitate corruption



<Figure 1> Network Visualization of Co-Occurrence of Keywords - Research on Biometric Technology

<Table 3> The Greatest Total Link Strength of The top 6 Keywords within the Domain of Biometric Technology

Keyword	
Security	138
Privacy	134
Authentication	100
Fingerprint	61
Identification	58
Surveillance	52

of author keywords (<Figure 1>). Our counting method was full. We set the minimum number of occurrence of a keyword to 5. Out of 6,622 keywords, 78 met the threshold. For each of the 78 keywords, the total strength of the co-occurrence links with other keywords was calculated; and the keywords with the greatest total link strength was selected. We then also selected the six top keywords with the highest total link strength. These keywords are: security, privacy, authentication, fingerprint, identification and surveillance (<Table 3>). This bibliometric analysis shows that data security, privacy, authentication and surveillance are key areas of concern in the field of biometric technology. Previous bibliometric and systematic qualitative reviews had acknowledged that some of the major challenges of IoT BDA are related security and privacy (Saheb, 2018; Saheb and Izadi, 2019).

Ⅱ. Research Model Development

However, the theories UTAUT, and HBM are among the popular models of adoption in the sports industry, very few studies have incorporated these theories in order to explore wearable based monitoring systems. Examining these theories in new and emerging technological contexts, such as wearable sensors, may lead to the creation of new knowledge. Unlike the original models, we made some modifications to these models on this research and combined them to better predict factors influencing athlete's acceptance of wearables.

In our study, we added a new construct called the perceived ethics. We asked the athletes about three main aspects of biometric data ethics: disclosure and confidentiality, privacy, and the security of their biometric data. We supported our argument regarding the importance of this predictor on the basis of previous studies exploring the ethics of biometric data and our scientomtric analysis of the biometric technology term. Of the UTAUT model, we added the three constructs of perceived usefulness, subjective norm, and reliability. Of the HBM model, we added health belief, perceived benefit, perceived threat, and perceived susceptibility. The rationale for selecting these variables was 1) addressing factors associated with *professional stressors and vulnerabilities* caused by the use of wearables (i.e., perceived usefulness, perceived threat, perceived benefit, perceived ethics); and 2) factors related to personal well-being reasoning (perceived susceptibility, health belief). For example, an athlete whose medal has been stripped because his / her biometric data confirms the incidence of doping. This paper did not include factors related to the underlying technical structure of the technology (such as perceived ease of use that deals with the effortless use of the technology). We added the reliability predictor to understand how athletes perceive the reliability of biometric data. To describe further, for instance, an athlete with a high interest in real-time monitoring may have strong intentions to use the technology. Likewise, an athlete who perceives that wearables will benefit his or her professional performance may have a strong intention of using wearables. Or an athlete who is under the social pressure of his / her coach may have less intention of using the technology. In this study, we only examine the behavioral intention, and we will not study the actual use behavior. Therefore, we did not include the attitude predictor. We also did not include moderators of gender, age, and voluntarism.

Ⅲ. Research Methodology

3.1. Neural Network Analysis vs Inferential Statistics

Previous researches on adoption and acceptance have employed advanced statistical modelling methods such as PLS or SEM to verify their research hypotheses (<Table 1>). Inferential statistics can estimate population parameters and test the significance of relationships between and among variables (Connaway and Powell, 2010). Inferential statistics is concerned with two major type of problems (i) the estimation of population parameters, and (ii) the testing of statistical hypothesis (Rajendra Kumar, 2008). Unlike this, predictive analytics, such as neural network modeling, involves with the use of mathematical algorithms and programming to discover explanatory and predictive patterns within data (Xu et al., 2018). Data mining aims to construct predictive models to identify useful correlated patterns and parameters to predict the occurrence of events based on past data (Jones, 2017). It includes techniques like neural network analysis. This method as a way of modelling human thought based on statistics and probability. After training data, this model has strong capability in predicting future (Loshin, 2012). Some recent studies on IT adoption has implemented neural network to predict user IT adoption; such as adoption of cloud computing (Priyadarshinee et al., 2017; Raut et al., 2018), remote health monitoring adoption (Huang, 2010), or social CRM adoption (Ahani et al., 2017). This research employs neural network modelling to predict the non-compensatory adoption of wearable sensors among male athletes.

3.2. Sampling and Data Collection

This study surveyed Iranian athletes. By professional athlete, we mean athletes and referees with high level of skills and job title. The survey was distributed to 500 athletes, and 450 completed the survey. Five of the surveys were incomplete, however, so we discarded them. As regards the age of the respondents, 222 respondents were between 20 and 29 years of age; 142 were between 30 and 39 years of age; 50 were between 40 and 49 years of age; 11 were between 50 and 55 years of age; 18 were between 19 and below; and 2 were between 60 and above. As far as their sports fields are concerned, 8 played volleyball, 45 swimming, 26 martial arts, 216 body building, 119 football, and 29 played other sports.

In order to recruit the respondents, we formed a social media group on the Telegram Platform, and, through this group, distributed the questionnaire among professional athletes from several major sports clubs in the Tehran Province. Only those professional athletes who used fitness wearables already to track their athletic activities were selected and joined the Telegram group. We also distributed a five-page paper describing the subject of the study to the respondents in order to increase their knowledge of the technology and study questions. We authorized the respondents so they could raise any question on the topic via the Telegram group.

<Table 4> Demographic Features of Respondents

Age	- 19 : 18 20 - 29 : 222 30 - 39 : 142 40 - 49 : 50 50 - 55 : 11 + 60 : 2
Gender	Female : 148 Male : 297
Sport	Volleyball : 8 Swimming : 45 Martial Arts : 26 Body Building : 216 Football : 119 Other sports : 29 Unknown : 2
Years of using the wearable:	1 year and less : 176 1 - 3 years : 236 3 - 5 years : 33 + 5 years : 0

3.3. Variables and Measures

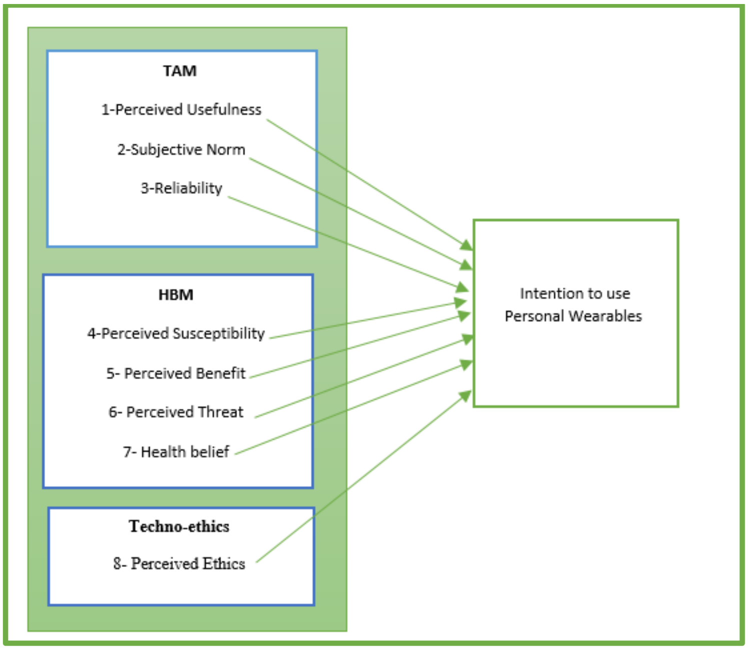
The 9 constructs in this research were measured by 39 questions (<Appendix>). Age and sport are single item measurements, but the other items are measured on the basis of the Likert 5-point scale. The UTAUT constructs (i.e., perceived usefulness, subjective norm, and reliability) are adopted from (Davis, 1985). The HBM constructs (i.e., perceived susceptibility, perceived benefit, perceived threat, and health belief) are adopted from (Green and Murphy, 2014); while the perceived ethics construct is derived from (Karkazis and Fishman, 2017) and the scientometric analysis conducted by the authors. The output variable of this research (i.e., intention to use wearable sensors by athletes) is adopted from (Davis, 1985). In regard to the perceived ethics construct, we followed the methodology offered by (Moore and Benbasat, 1991) to develop the measurement scales by asking five experts (full professors in MIS) to express their opinion on appropriate items for inclusion. We carried out two stages to develop the "perceived ethics" construct. The first stage was conceptualization in which we developed the measure concept of "perceived ethics" based on the findings of the co-word analysis described earlier in the paper. We asked five full professors in the IS departments of Tehran University and Tarbiat Modares University and asked for their input about the name of the construct. They all agreed on the name of the construct. The next stage was scale development to assess the construct validity stage. We inquired our panel of IS experts on how to measure the construct by evaluating the questions. The experts modified the sentences to make them more transparent. We used the same standard questions that are used in the UTAUT and the HBM models with some modifications to address the adoption of wearables. We added the new construct of "perceived ethics" in order to highlight the ethical concerns of biometric data. Under the category of perceived ethics, we inquired the following questions to assess the perception of data disclosure by athletes and the security, and privacy of data produced by their personal wearables:

1- Wearables will increase the disclosure of my secret information.
2- Wearables will intrude my privacy by sharing my private physiological data.
3- Wearables are not secure enough and my physiological data can get hacked.

3.4. Reliability and Validity Measures

In this research, we used Excel 2016, and SPSS 24 sofware to measure the reliability and validity of variables. In order to assess the degree of consistency between multiple measurements of variables, we evaluated the Cronbach Alpha; which assesses the consistency of the entire scale. The Standardized Cronbach's alpha for this research is 0.848, which indicates a high level of internal consistency (Hair et al., 2013). In order to define the underlying structure among the variables in our analysis, we conducted factor analysis to understand which variables best predict intention to use biometric technologies among athletes. As <Table 4> shows, the composite reliability is 0.814. Fornell and Larcker said that if the composite reliability is higher than 0.6, the convergent validity of the construct is adequate (Fornell and Larcker, 1981).

From <Table 3> and <Figure 2> on rotated component matrix, we can see that the first component is highly related to the following variables: perceived usefulness, perceived ethics, perceived threat, and perceived benefit. These variables can reflect a more general evaluative dimension of "Perception of Professional Stressors". Perceived usefulness highlights how the technology will improve the performance of the athlete's job. Perceived ethics, threats and benefits are also concerned with the ethics, threats and benefits of using technology for the professional life of an athlete. The second component is highly related to the subjective norms and health knowledge and health belief, which may reflect a more general evaluative dimension of the "Reasoning Framework" of an athlete health status. After the Varimax rotation,



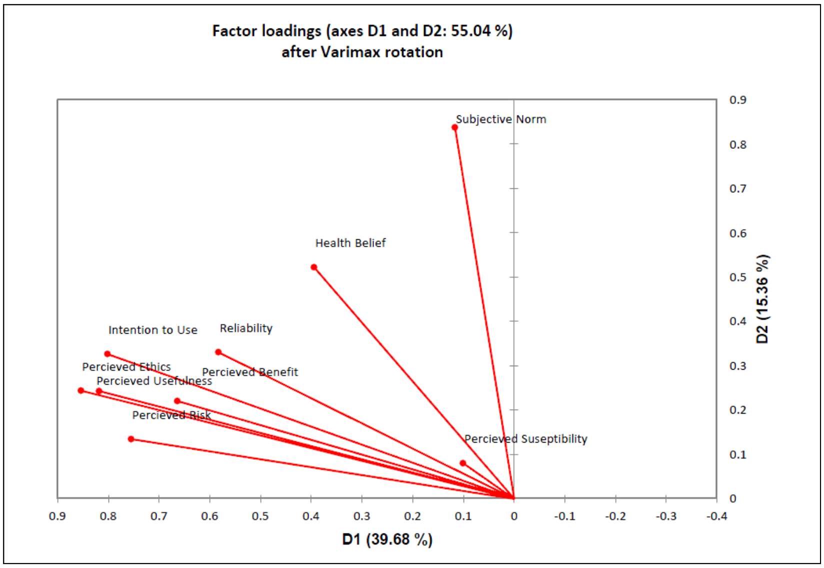
<Figure 2> Research Model of the paper

the two factors account for 55.04% of the total variance, which is satisfactory.

Ⅳ. Data Analysis and Results

We used the RapidMiner 9.0 software to conduct the back-propagation neural network to build our model. The backpropagation algorithm is a highly efficient methodology that works with derivatives to find the optimal parameters (Kuhn and Johnson, 2013). We applied the back propagation algorithm to the multilayer perceptron. A multilayer perceptron consists of an input layer, one or more hidden layers and an output layer. The perceptron maps continuous predictors for a binary outcome and the perceptron deterministically reports that Y = 1 or Y = -1 (Neapolitan and Jiang, 2018). In this method, we assigned values between 0 and 1 to the initial weights and biases. We then provided the model with sets of inputs, which are UTAUT variables, HBM variables and biometric data ethics. The output will be the intention of athletes to adopt wearables.

<Figure 3> shows the process of building and validating the neural network model that we developed for this research. To develop this model, we set one 10 sizes hidden layer. The neural net operator was sigmoid function, acting as an activation function. The value range of the attributes should therefore be scaled to －1 and + 1. This was done using the normalize parameter. We also opted for the Shuffle sampling option. It indicates that the input data should be shuffled before learning. We set the learning cycle to 500. As it is described in the manual of the software, in back-propagation, the output values are compared with the correct answer to compute the value of some predefined error-function. The error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of



<Figure 3> Factor Loading After Varimax Rotation

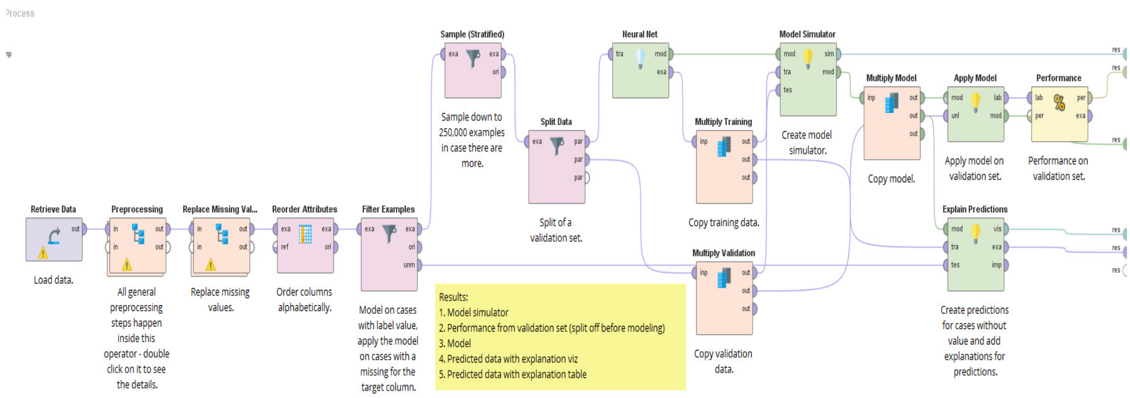
<Table 5> Factor Loading and Composite Reliability

	Factor Loading after Varimax Rotation λ	λ^2	1-λ2
Health Belief	*0.418*	0.174724	0.825276
Perceived Benefit	***0.704***	0.495616	0.504384
Perceived Ethics	***0.905***	0.819025	0.180975
Subjective Norm	*0.124*	0.015376	0.984624
Reliability	***0.618***	0.381924	0.618076
Perceived Usefulness	***0.868***	0.753424	0.246576
Perceived Threat	***0.801***	0.641601	0.358399
Perceived Susceptibility	*0.107*	0.011449	0.988551
COUNT	8	8	8
SUM	4.545	3.293139	4.706861
SQUARE	20.657025		
Composite Reliability	**0.814426662**		

Note: *P* value of all variables is 0.00, which is less than 0.05

the error function by some small amount. In our study, this process is repeated 500 number of times. We set the learning rate to 0.01; the momentum to 0.2, and the error epsilon to 1.0e-5.

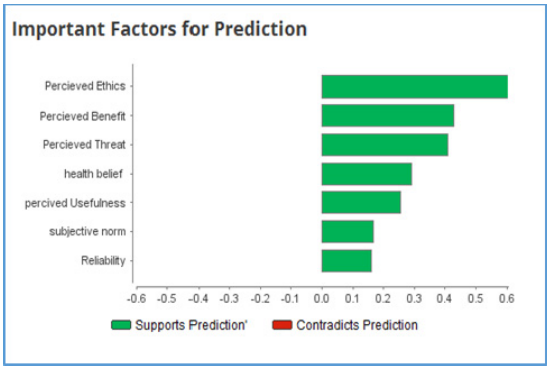
We conducted multiply validation on the split data. The ratio of partitions was 0.8 and 0.2. The validation shows that the prediction of the model is 3.536. The biggest support for this decision comes from per-



<Figure 4> Process of Buidling and Validating the Neural Network Model of the Research on RapidMiner

ceived ethics. The Root Mean Squared Error (RMSE) of all predictions done by this model is 0.462. And the relative error is about 9.78%. We can therefore be confident that the network model is reliable in capturing the numeric relations between the inputs and the output. The standard deviation for the model is +/- 0.000. The less the standard deviation, the more stable the model is, given its higher accuracy. The squared correlation is also 0.661, with a correlation of 0.813.

<Figure 4> shows that, based on neural network modeling, the most important predictors for the adoption of wearable sensors by athletes are perceived ethics, perceived benefit, and perceived threat. Of



<Figure 5> Important Factors for Prediction Based on the Neural Network Modeling

the variables of the UTAUT theory, the perceived usefulness has more value than the other variables of the UTAUT model. Of the HBM variables, the perceived susceptibility has zero impact. Of the UTAUT, the subjective norm is not a strong predictor either. Overall, the results suggest that it is important to broaden existing adoption models by including the variables of ethics, threat, benefit and usefulness.

Ⅴ. Discussion and Implications

Development of real-time monitoring platforms based on wearable technologies (Glaros et al., 2003) and the development of sensor-fusion methods to combine many streams of physiological data is becoming one of the fast-growing trends in the sports industry. These integrated systems (Seshadri et al., 2017) monitor the physiological status of athletes non-invasively (Matzeu et al., 2016). Our model shows that the professional stressors of perceived ethics, perceived benefit, perceived threat are the strongest predictors of wearables adoption among athletes. This finding is in consistent with previous studies that have confirmed the important role of perceived threats (Guo, 2010; Kesharwani and Singh

Bisht, 2012; Walter and Lopez, 2008), perceived benefit (Alhakami and Slovic, 1994; Lee, 2009) and perceived usefulness (Cheng and Mitomo, 2017; Mou et al., 2017) on technology adoption.

In this study, we extend the literature on UTAUT by adding a new predictor called the perceived ethics in order to address the security and privacy of their own physiological data, and real-time surveillance developed by using fitness wearables. It is worth mentioning that some studies argue that there are two similar risks when people adopt technology (i.e., risk to their own lives and risk to the privacy of others). In one study, the authors argue that the perception of risks to other people's privacy has a significant impact on the adoption of technology (Rauschnabel et al., 2018). In this study, however, we focused solely on athlete's perception of risks imposed to their own professional life. Exploring how athletes' perception of risks to the life of the other athletes also influences their technology adoption is worthy of research. In our study, perceived threat / risk examined risks imposed to the professional life of athletes using wearables; while perceived ethics focused on ethical challenges associated with wearables; such as violations of private data of athletes, hacking of personal data (i.e., security), and surveillance challenges.

This research shows subjective norm of the UTAUT theory is not a strong construct to predict the adoption of wearables among athletes. This research also shows that the predictive power of perceived usefulness of the UTAUT theory is stronger compared to the other UTAUT variables. As opposed to the UTAUT, most of the HBM variables can predict the adoption of wearables among athletes. These variables are perceived benefit, perceived threat and health belief. In contrast to these variables, perceived susceptibility has zero prediction strength. This study shows that the prediction strength of perceived ethics is greater than that of other variables. These findings are in line with the claims that adoption theories should be modified when examining various contexts (Venkatesh et al., 2011; Venkatesh and Bala, 2008). In the context of wearable sensors, it is useful to understand the perception of individuals about ethical challenges and their impact on technology adoption.

This research has responded to the recent recommendations in information system and ethics of technology literature. Recent scholars have pointed out the shift from traditional technology adoption models to the development of new predictors. On the other hand, the literature on technology ethics highlights the emerging ethical challenges of technologies that generate biometric data for their users. This research responds to these two inquiries by integrating the UTAUT model with the HBM theory and ethics of biometric data.

5.1. Key Theoretical Contributions and Implications

The first major theoretical contribution of this research is a better understanding of wearables adoption by athletes via developing a predictive neural network model to predict the adoption of wearable sensors among athletes. This model integrates variables from MIS, ethics, and health informatics to better understand the relative importance of variables influencing the adoption of wearables. Our findings have shown that the most important factor for the adoption of wearables is the user's perception of the ethical challenges of biometric data. These challenges include disclosure of their data, intrusion into the privacy of their data, and security challenges related to their personal biometric data. Previous studies on the adoption of wearables have neglected users' perception of the ethics of the biometric data. As a result, the predictive power of other IT adoption models, especially technologies dealing with users' personal data, can be improved by integrating this variable. Theories on the ethics of biometric data and also the analysis of the co-occurrence scientific keywords can provide a useful framework for studying the relevant challenges of "perceived ethics;" as this research shows that perceived ethics is an important predictor.

The second theoretical contribution of this research is associated with the health informatics and the real-time monitoring of athletes. While wearable sensors have been used for patient monitoring, their use in athlete monitoring has remained sparse. It will also supplement previous work on real-time monitoring and wearable adoption by developing this research model, derived from theories of UTAUT, ethics, and HBM. Our analysis shows that most of the HBM model variables (i.e., perceived benefit, perceived threat, and health belief) have a different but strong impact on wearables adoption. Perceiving more threats as a consequence of using the wearables, for example, may potentially affect the adoption by the athlete. Before implementing any real-time monitoring device based on wearable sensors these aspects have to be considered. For example, athletes should be clearly informed about the potential benefits and threats of wearable real-time monitoring systems. This study shows that perceived susceptibility is the least important factor in the HBM model. This means that the perception of athletes as to their susceptibility to a disease will not influence their adoption of wearables. As far as the UTAUT variables are concerned, the least important factors are the subjective norm and reliability. This means that athletes are less likely to adopt wearables if they are under the pressure of close people around them; or their perception of the reliability of wearables has a minimal impact on their adoption.

The most recent theoretical implications of this research are the use of predictive neural network modeling for the study of wearable adoption. Previous studies have recommended the use of neural network as a predictive analytics approach. In response, this study proposes a predictive neural network model. This model shows that the integration of perceived ethics and most HBM variables can strongly predict the behavior and intent of the individual, particularly in the adoption of technologies that generate biometric data.

5.2. Key Practical Contributions and Implications

This study has several practical contributions and implications. In this study, we only mention the most important ones. The sports industry is introducing wearable sensors for the real-time monitoring of athletes; however, there is legal consideration in the processing of biometric data. In order to ensure the protection of athletes, comprehensive legal frameworks and policies should be developed with regard to the privacy and security of the personal biometric data of athletes. On the other hand, the athletes, as the data subjects, would have specific legal rights about their personal data

The study showed that perceived benefit and threat are strong predictors. Teams and organizations need to provide comprehensive educational courses and awareness campaigns for athletes about the advantages and risks of using wearables. The other big practical consequence is the limitation of security violations and the selling of athletes' personal identifiable information to the black market by establishing effective security standards and security governance frameworks.

5.3. Future Studies

This study has several limitations as well. The first is that this research is carried out in the context of Iran; hence future research should study various countries and different social contexts. The second limitation is that in this study, we used the neural network to predict the most important variables, and so we did not propose any hypotheses to determine the causal relationship between the predictors and the output variable. Future studies can apply both neural network and other techniques such as structural equation modeling to test the hypotheses of their research We recommend that future studies with large data samples can apply deep learning algorithms, as this predictive modeling has more hidden layers, can be trained in both supervised and unsupervised ways, and can also offer prescriptive modeling. Other future studies can also wearables from a fashnology perspective(Rauschnabel et al., 2016). Previous studies show that people tend to incorporate other people's privacy concerns more than their own (Rauschnabel et al., 2018), so one possible future study is to understand this phenomenon among the professional athletes.

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<Appendix> Measurement Items

Constructs and their Operational Definition
Health Belief
1. I have much interest in real-time monitoring of my physiological condition.
2. I attentively implement real-time monitoring of my health.
3. I am willing enough to implement real-time monitoring of my health.
4. Now I actively implement real-time monitoring of my health.
Perceived Benefit
1. I am sure that physiological data of my personal IoT will be used to promote my professional life.
2. I am sure that physiological data of my personal IoT will be used to improve my weak points of my professional life.
3. I am sure that physiological data of my personal IoT will be used to strengthen the strength points of my professional life.
Perceived Ethics
1. Wearables will increase the disclosure of my secret information.
2. Wearables will intrude my privacy by sharing my private physiological data.
3. Wearables are not secure enough and my physiological data can get hacked.
Subjective Norm
1. My coach and investors influence my behavior for health management through using a personal IoT.
2. When my team-mates implement health management through personal IoT, I feel a sense of rivalry to do better.
3. I think I do not need pressure of my coach and investors to use personal IoT. I am aware of its benefit.
4. I think I am more aware of wearable sensors compared with my other team-mates.
5. I think I am aware of wearable sensors to a certain extent compared with my coach and investors.
Reliability
1. It is credible to use personal wearables for provision of real-time monitoring of physiological status.
2. Contents of personal wearables or provision of real-time monitoring are reliable.
3. Contents of personal wearables for provision of real-time monitoring are professional.
4. Findings of personal wearables for provision of real-time monitoring and health management are of acceptable quality.
5. Findings of personal wearables for provision of real-time monitoring and health management are easily understandable.
Perceived usefulness
1. It is an economic way to find real-time monitoring using IoT technology.
2. Real-time monitoring via IoT has improved my understanding of my health status in my professional life.
3. Real-time monitoring via IoT has improved my capacity for health management in my professional life.
4. Real-time monitoring I found an IoT app has influenced my professional life in a good way.
Perceived Threat
1. I am afraid that physiological data of my personal IoT be used against my professional life.
2. If physiological data shows abnormalities in my health status, I will get restrictions by my coach.
3. If physiological data shows abnormalities in my health status, I will be fired from the team.
Perceived susceptibility
1. I do not have a likelihood of experiencing a physiological problem negatively influencing my performance.
2. There is no person with serious physiological problems among my family members.
3. I do not have a strong possibility of health attack due to improper daily habits.
Intention to use
1. I will continue using my personal IoT to get physiological data
2. I will regularly use it to get physiological data.
3. I will recommend using it to my other team mates.
4. I will share my personal physiological data to my coach
5. I will share my personal physiological data to academic institute.

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