11 Years with Wearables: Quantitative Analysis of Social Media, Academia, News Agencies, and Lead User Community from 2009–2020 on Wearable Technologies

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The role of wearable technology in our daily lives is rapidly growing and many users are cumulatively becoming dependent on it. To provide insight into the future of wearable technologies and various community attitudes towards them, we implemented an in-depth quantitative investigation of opinions from academic texts (DBLP and PubMed), social media (Twitter), news media (Google News and Bing News), and entrepreneurship communities (Kickstarter and Indiegogo) over a 10-year period. Our results indicate that unlike academia, the news media, entrepreneurship communities, and social media all hold overall positive attitudes towards wearable technologies. Secondly, there are diverse perspectives towards various wearable products across different platforms. Specifically, "XR" technologies received the most attention, while "Exoskeleton" ignited the most heated debates. Thirdly, we discovered that the lifetime of a hyped wearable technology lasts approximately three years. Furthermore, the news media and entrepreneurship community's attitudes towards wearable technologies did not have a strong impact on public opinion. Finally, among all types of wearable technologies, "fashion design" and "healthcare" products were the most enlightening for the market.

CCS Concepts: • **General and reference** → **General conference proceedings**; • **Social and professional topics** → **Industry statistics**.

Additional Key Words and Phrases: wearable technology, market analysis, text mining, sentiment analysis

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1 INTRODUCTION

Wearable technologies are a new type of human-computer interaction paradigms which use computing power to drastically improve the user's perception of the environment and aid in acquisition of their status, and thus, play an irreplaceable role in improving user quality of life. These technologies cover a wide-range of electronics categories, including devices intended to be worn as clothing, accessories, or even implanted into the user's body. Khakurel et al. [54] define wearables as electronic computing devices which are either integrated into or connected to the human body in some capacity to effectively detect and analyze vital signals. Dehghania et al. [27] further define wearables as "embedded portable computers". The foundation of wearable computers is attributed to the invention of the wristwatch in the 16th century [2]. Specifically, Thorp [98] invented the first completely operational wearable computer in June 1961. From the initial wristwatch concept to the first wrist-mounted commercial product, the Casio Databank watch, the progression of wearable devices closely followed technological advancements [75]. As a result, wearable devices developed from featuring a single display to including a wide variety of wrist-mounted computing devices with smart displays. As an intricate combination of electronics, software, user interfaces, sensors, smart applications and contemporary designs, modern wearables represent not only technological innovations but also fashionable products. [21].

A recent study [25] on wearable technologies highlights the increased demand for the miniaturized technology. Furthermore, Gartner Inc. [38] predicted that the wearable computing market is expected to reach up to $52 billion by the end of 2020, with projected total sales of over 150 million units of wearable technology products. Similar to previous studies, our analysis displayed a predictable pattern of growth until the COVID-19 pandemic and lockdown of early 2020. Following the economic turmoil due to the pandemic, different community attitudes toward wearables have shifted, making any effort to justify the impact of wearable technologies premature.

Although the wearables market is undergoing rapid proliferation, the effects of wearable technology adoption and consumer psychology is relatively poorly understood when considering the complex landscape and the presence of various communities and stakeholders [74]. Since public demand shapes the future of the wearable technology industry, the entrepreneurship and academia should understand public preferences and seek to quantify their trends and behaviors over time. Several challenges were identified in wearable technology industry, including hardware design challenges [14, 53, 86], data accuracy [35, 88], privacy [85], customer loyalty [44], device compatibility [62], software design and usability [50, 55], battery limitations [45, 86], and user applicability [39]. This work gathers insight from these various perspectives and aims to provide a holistic overview of wearable technologies.

On the other hand, the impact of news media cannot be ignored, as it has the ability to shape public opinion [12]. We seek to identify potential connections between news media attitudes and public attitudes towards wearable technologies, and whether news media sentiments affect the prevalence of wearable technologies in the general public. However, simply understanding which wearable technologies are favorable is not sufficient; it remains important to identify the unique segments of the wearable technologies market that the consumer electronics industry focuses on as well as other sectors, including healthcare [108], educational tools [6], fashion (in wearables) [13, 81], entertainment [110], fitness [64], and more.

In this paper, we perform an integrative quantitative analysis on different sectors and communities of wearable technologies. We employ datasets from news media, social media, entrepreneurship communities, and academia. Our study has five limitations, including Twitter datasets which only feature two years of data, and these will be described later.

The three main contributions of our paper are as follows:

- It provides a holistic overview of wearable technology in the last decade. There are promising works which analyze wearable technologies in specific segments, such as healthcare [116], or specific technologies, such as Cross Reality (XR), which is an umbrella term for reality-assisted immersive human-machine interaction technologies and includes virtual reality, augmented reality, and mixed reality. [76, 94]. To our knowledge, a holistic overview which has quantified community-specific differences in perspectives of various wearable technologies has not yet been published.

- Our work identifies different communities' opinions regarding specific wearable technologies. A quantitative analysis of community opinions could help researchers, market analysts, and developers to better understand which segments of wearable technology require further investigation and improvements. There are promising studies which use data from social media or news media for product analysis [93] and political opinion mining [5]. However, few studies have employed such a variety of platforms to quantify opinions of a specific technology.
- This work estimates a lifetime of favor for each wearable technology, which leads to identifying wearable technologies that receive less attention from news media and academia, but have higher demand as measured by public opinion (Twitter users). These findings will enable investors and researchers to identify under-explored opportunities in the market.

2 RELATED WORK

With advancements in emerging technologies (e.g., artificial intelligence), wearable technologies are developing and diversifying rapidly. The public's adaptability [31, 32, 100], adoption, and acceptance [28, 33, 71] of wearable technologies may influence market structure as well as future directions. Therefore, to understand the public's adaptability and acceptance of these technologies, it is critical to gain a comprehensive understanding of their concerns and expectations regarding the wearable technology market. In this section, customer evaluation of two aspects of the merits of a product will be discussed, which include perceived value and technology characteristics analysis via web data. Furthermore, background on paper-specific techniques with regards to public data collection will be provided.

2.1 Perceived Value

Yang et al. [113] define perceived value of wearable devices as a potential customer's overall perception based on device benefits and costs. According to Scott [93], perceived ease-of-use (PEOU), or "*the degree to which a person believes that using a particular system would be free of effort*" and perceived usefulness (PU), defined as "*the degree to which a person believes that using a particular system would enhance his or her job performance*" are the two fundamental measurements of perceived benefits. Both intrinsic and extrinsic perspectives of consumer PEOU and PU of wearable devices [74], activity tracking [44, 65], virtual reality in healthcare [52], and wearable health technologies [16, 20] have been investigated and verified. As such, manufacturers are continuously releasing wearable products or defining future specifications [84]. However, consumer adaptability and acceptance of wearable devices is still changing. Therefore, an introduction of key factors which can sway consumer acceptance of wearable technologies is required.

Perceived risk (PR) is one factor consumers consider when using wearable devices. According to Cox and Rich [24], PR refers to the nature and amount of risk perceived by a consumer contemplating a particular purchase decision. Kalantari [51] reaffirms that consumer perception of potential risk on individuals is a significant barrier for adoption of wearable technologies.

Previous research identified that perceived risk hinders the adoption of wearable technology [97]. Specifically, one of the main obstacles is the inaccurate measurement of data, such as vital signs collected from wearable sensors [83, 102]. Moreover, financial risk originating from the cost of the devices may hinder a consumer's acceptance of the product. Horton [46] conceptualizes the possibility of net financial loss to a consumer due to impairment, replacement, and refund of a product. Buenaflor and Kim [41] also suggest that the individual's feeling of comfort and security in accessing and sharing their data is an important factor in the acceptance of a wearable device. Some other aspects of risk include failure of a product, such as performance risk and potential physical injury resulting from product use [58].

2.2 Market Analysis from the Web

Users enjoy novelty, freshness, and excitement, and wearable AR enhances experiences through the provision of additional visual information [99]. As such, virtual and augmented reality can be used to enhance museum visits, as well as other activities [3]. Several studies demonstrated that wearable technology is increasingly applied in a wide variety of industries and disciplines, including the military [8], construction industry [117], and medical science [29]. With the rise of big data and machine learning techniques, wearable technology will soon be interpreted under broader definitions, a wider range of coverage, and a wider group of beneficiaries. As a result, wearable devices have the potential to set off a popular revolution [77]. Rogers' *Diffusion of Innovation* theory explains how one specific factor affects momentum and diffusion of a specific product over a particular social community [91]. This theory was widely replicated in various contexts to analyze the wearable technology market using different models, such as the *Technology Acceptance Model* (TAM) [47, 51, 57] and the *Unified Theory of Acceptance and Use of Technology* (UTAUT) [102, 110]. Wearable technologies are not only IT innovations, but they are also fashion products. Coorevits and Coenen [23] described that perceived aesthetics such as unique designs, colors, and textiles can contribute to consumer decision-making, since wearables are visible to other people. The comfort of a wearable device is another factor that is critical for its acceptance. According to Arvanitis et al. [4], perceived comfort and potential harm, emotion, and restricted movement of the consumer should be taken into account to increase market acceptance of wearables. Canhoto and Arp [15] further state that visibility of distinctive wearable devices can make consumers proud to wear them and thereby expand adoption of the product. Additionally, Nasir and Yurder [70] discovered that compatibility of users need with wearable health technologies is a critical aspect for the broader adoption of wearable devices.

Considering the widespread availability of public data regarding wearables, this work combines Rogers' Diffusion of Innovation theory and information retrieval, text mining techniques to analyze the current status of wearable technologies. Previous studies incorporated data mining in their market analysis framework to examine market opportunities in different business sectors, such as stock trading strategies using Twitter data [105], stock sentiment analysis using Twitter data [7], evaluation and management of healthcare [17], customer relationship management [103], student retention management [112], and future robot impact on society [49].

3 METHODS

In this section, we first introduce the datasets which were used and provide details about the implementation of our methodology. Inspired by previous work in social computing [1, 17], three methods were implemented in our study, which include bibliometrics [80], topic modeling (Latent Dirichlet Allocation, LDA) [11], and sentiment analysis [101]. To allow full reproducibility, all of our code is open-source and freely available.[1]

3.1 Datasets

We targeted six web platforms and grouped them into four different sectors, each representing opinions from diverse fields, such as news media platforms (Google News and Bing News), social media (Twitter), entrepreneurship communities (Kickstarter and Indiegogo), and academia (limited to computer science[2] and biomedical science[3]). To collect relevant texts, we first extracted keywords related to wearable technologies. Three individuals searched the term "wearable" using the Google and Bing search engines and analyzed the title and subtitle of the first 100

[1] https://github.com/Jackymeister/Wearable-Technology
[2] DBLP, https://dblp.org
[3] PubMed, https://www.ncbi.nlm.nih.gov/pubmed

Table 1. Number of records in datasets before and after filtering

Sector	Platform	Initial Records	Filtered Records	Total Records
Academia	DBLP	2,168,003	5,992	16,101
	PubMed	10,940,596	10,009	
Entrepreneurship	Kickstarter	2,348	2,347	3,106
	Indiegogo	4,255,076	759	
News Media	Google News	119,698	112,101	125,152
	Bing News	60,298	13,051	
Social Media	Twitter	1179,265	624,717	624,717

websites listed. One annotator was the author of this paper, and the other two were employed and compensated by the company which provides us news media, Twitter, and Kickstarter data. In total, a set of 42 keywords was identified from different categories of wearable technology. Next, unrelated keywords (e.g. stretchable wearables, smart fashion, etc) were removed and the remaining keywords were evaluated, resulting in a near-perfect Fleiss' kappa [36] score (∼ 95%). As a result, 36 keywords[4] were kept for analyses. The identified keywords were used with the eMentalist[5] web crawling API to construct the dataset with data from Google News, Bing News, Twitter, and Kickstarter. Furthermore, Indiegogo data provided by Web Robots[6] and academic publications extracted from DBLP and PubMed were cleaned using Python version 3.7.0. The data cleaning process retained entries containing keywords and removed duplicate entries. Each entry in the cleaned dataset featured the content of the post in text format, its creation timestamp, and the platform from which it was collected. Table 1 shows a combined summary of various data sources; Table 2 presents the frequency of all keywords from 2009 to the end of June 2020 for each group. Since some data objects were labeled with more than one keyword according to the text, each keyword in the text was counted.

3.2 Bibliometrics

To provide further insight, a bibliometric method was employed on the academia dataset, which allowed our team to gain insight into the timeline of development and advances in each type of wearable technology. Bibliometrics refers to the analysis of academic data which assists researchers in recognizing "hidden patterns" by classifying information according to keywords and publication dates [26, 95]. We used a dataset of papers published between 1936–2020 in the fields of computer science and biomedical science. The most frequent keyword to appear in the academic papers was "wearable", followed by "XR". The number of entries prior to 2009, however, was relatively small, which may lead to uninterpretable results. Therefore, all entries prior to 2009 were discarded our final dataset comprised 16,101 entries. Figure 1 presents the frequency of each keyword for both DBLP and PubMed databases. Figure 2 describes the number of publications in academia based on three major topics in a ten-year period. Since data was only obtained for the first six months of 2020, to have a fair comparison we multiply our 2020 data by a factor of two (to create a synthetic overview for 2020). This processing may introduce some bias for the 2020 dataset, but in the scope of the overall study, this bias will be negligible.

[4]Keywords: Augmented Reality, Body Gadget, Body Robot, Brain-Computer Interface (BCI), Digital Bracelet, Digital Cloth, Digital Goggle, Digital Necklace, Digital Prosthesis, Digital Ring, Digital Shoes, Edible Robot, Exoskeleton, Fitness Tracker, Head Display, Head Wearable, Head-mounted Display, Intelligent Cloth, Mixed Reality, Smart Band, Smart Bodywear, Smart Bracelet, Smart Clothes, Smart Glass, Smart Goggle, Smart Necklace, Smart Patch, Smart Prosthesis, Smart Ring, Smart Shoes, Smart Suit, Smart Tattoo, Smartwatch, Virtual Reality, Wearable, Wrist Worn
[5]https://www.ementalist.ai
[6]https://webrobots.io

Table 2. Keyword Counts for each group.

Keyword	Academia	Entrepreneurship	News Media	Social Media
Augmented Reality	2212	470	1367	61668
Body Gadget	0	1	1184	1146
Body Robot	0	10	517	14992
Brain-Computer Interface	1132	0	41744	368
Digital Bracelet	0	2	1548	1434
Digital Cloth	0	14	1281	962
Digital Goggles	0	0	872	577
Digital Necklace	0	3	1201	441
Digital Prosthesis	0	0	896	2
Digital Ring	2	6	1199	6853
Digital Shoes	0	3	1136	3204
Edible Robot	1	0	999	112
Exoskeleton	1112	33	995	22779
Fitness Tracker	29	63	1046	36770
Head Display	0	0	59887	2337
Head Wearable	0	0	124	272
Head-mounted Display	236	0	5743	79
Intelligent Cloth	3	3	1289	307
Mixed Reality	344	59	1122	30482
Smart Band	9	26	1116	29375
Smart Bodywear	0	0	1513	3
Smart Bracelet	6	27	1050	19997
Smart Clothes	22	31	999	1822
Smart Glass	47	41	1305	14231
Smart Goggles	0	2	823	1310
Smart Necklace	0	5	1136	931
Smart Patch	7	6	1077	3747
Smart Prosthesis	2	27	1060	19361
Smart Ring	5	16	1076	14407
Smart Shoes	7	9	1137	13887
Smart Suit	2	1	970	2682
Smart Tattoo	4	0	215	2
Smartwatch	124	290	1223	64410
Virtual Reality	4932	772	1515	82253
Wearable	5871	1296	1605	66712
Wrist Mounted	1	6	740	1116

3.3 Topic Modeling

We used a topic modeling algorithm to observe and cluster potential relationships between texts collected from each platform. Firstly, we labeled textual data manually at their optimal number of topics where the coherence scores were the greatest. Afterwards, identified topics were treated as features for sentiment analysis. With the extensive textual dataset we employed, it was difficult to use qualitative methods to classify these data. Therefore, we used a topic modeling method known as Latent Dirichlet Allocation (LDA), which identified and clustered underlying structures among the data.

LDA, proposed by Blei et al. [11], was an unsupervised topic modeling technique, which featured a Bayesian probability model that contained a three-layer structure of words, topics, and documents. Each word inside a post was obtained by selecting a specific topic with a certain probability and selecting a particular word from that topic with a known probability. The processes of distributing documents to topics and topics to words followed

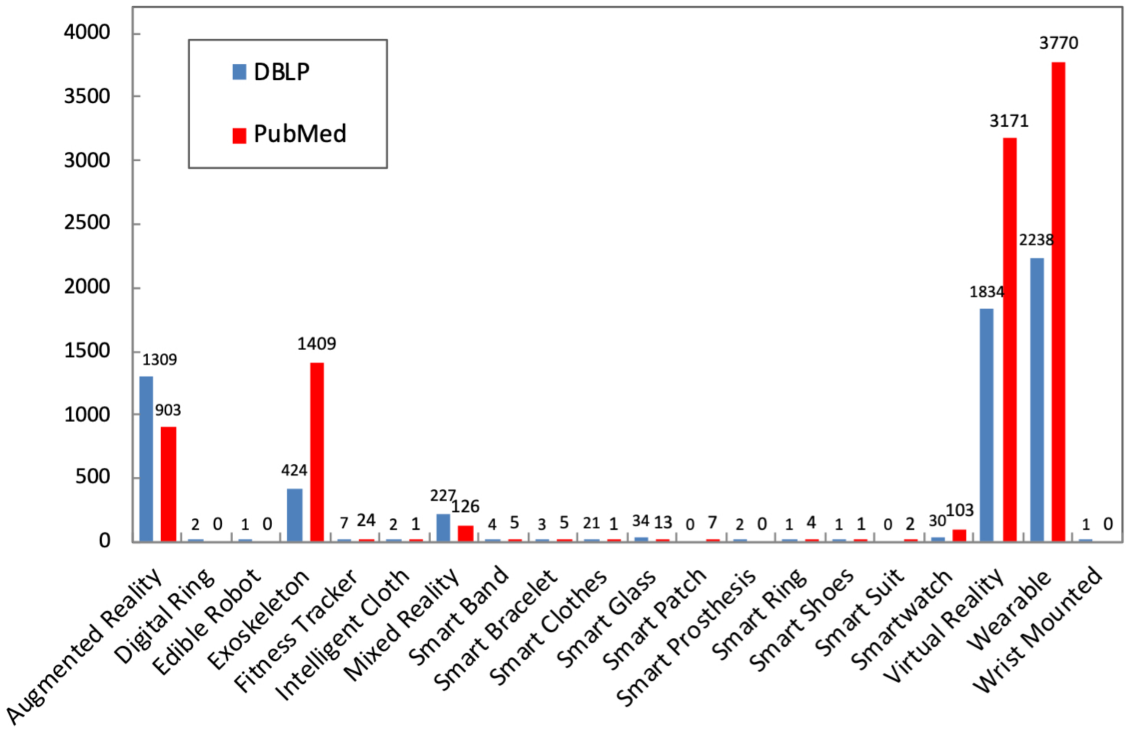

Fig. 1. Keyword distributions in DBLP and PubMed

polynomial distributions. Unlike clustering algorithms, LDA did not incorporate any distance metrics to measure distances between topics; instead, it assigned each document a mixture of topics and each topic was assigned a specific weight. The topic with the greatest weight was set as the *featured topic* for each document (i.e. each post in our dataset), and this featured topic was used for further sentiment analysis.

3.4 Sentiment Analysis

Natural language processing (NLP) is a field of research at the nexus of linguistics, computer science, engineering, and artificial intelligence. Furthermore, a widely used application of NLP is sentiment analysis, which helps individuals to quickly obtain and organize information about user opinions on a topic. Sentiment analysis has been widely used in several disciplines to study the dynamics of a phenomenon, such as entrepreneurial news reports analysis [106], university ranking, [48], public issues [56], and scientific conversation [61, 66]. Sentiment analysis can also be used to compare different sectors' opinions, such as news versus public media [49]. In this study, sentiment analysis processes, summarizes, and allows inference about users' subjective opinions and emotions to help investors and researchers better understand the attitudes of different communities with regards to wearable technologies.

To that end, we used the transformer model proposed by Vaswani et al. [104]. Specifically, we implemented the Bidirectional Encoder Representations from Transformers (BERT) baseline model proposed by Devlin et

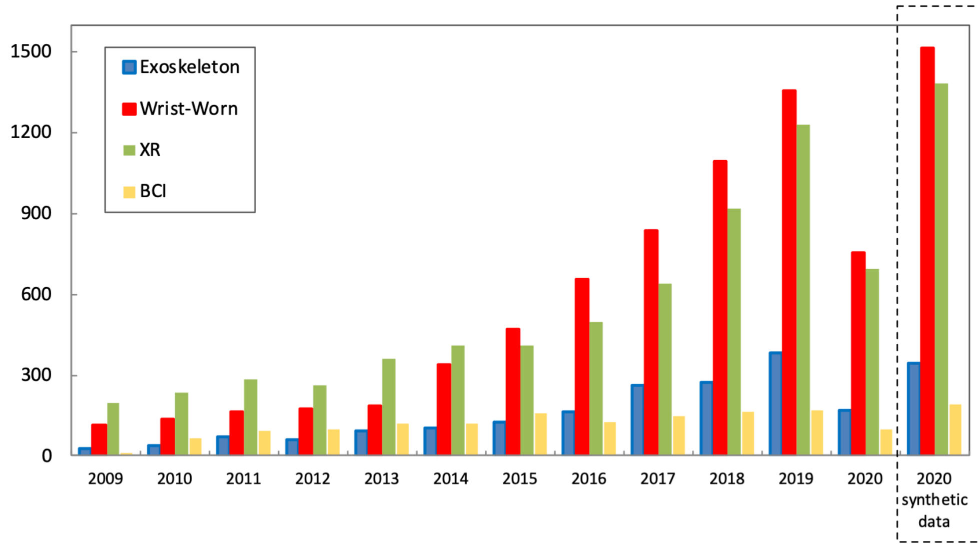

Fig. 2. Trend of Topics mentioned most in Academia. Since we do not have access to the entire 2020 dataset, we multiply the available data by a factor of two. The dotted column was added synthetically to simulate the growth of wearable content by the end of 2020.

al.[30], which is a state-of-the-art language representation model. Unlike OpenAI GPT[7], which uses a left-to-right transformer, and ELMO[8], which independently trains concatenation of left-to-right and right-to-left Long Short-Term Memory (LSTM) to generate features for downstream tasks, BERT uses a bidirectional transformer. More importantly, the BERT transformer uses a bidirectional self-attention mechanism called a "Transformer Encoder", while the GPT Transformer uses restricted self-attention, in which each token can only handle the context on its left.

To employ BERT for our application, we used the pre-trained transformers created by Thomas et al. [109] as the embedding layers. Since the transformer is pre-trained, we froze the transformer and trained a two-layer bidirectional gated recurrent unit (GRU), which learned contextual token representations from the transformer enabled by a masked language model (MLM). Figure 3 describes this model.

3.5 Experiment

In this section, data cleaning and preprocessing is first described, followed by LDA implementation and LDA fine-tuning across all six web platforms. Finally, details regarding implementation of BERT sentiment analysis on all platforms are provided.

3.5.1 Data Cleaning and Preprocessing. As described, we used two tools to achieve our goals, which include topic modeling and sentiment analysis, both of which require extensive preprocessing and cleaning of the data. As this study focused on textual data and the corresponding year from each data source, other metadata information

[7]https://openai.com/blog/better-language-models
[8]https://allennlp.org/elmo

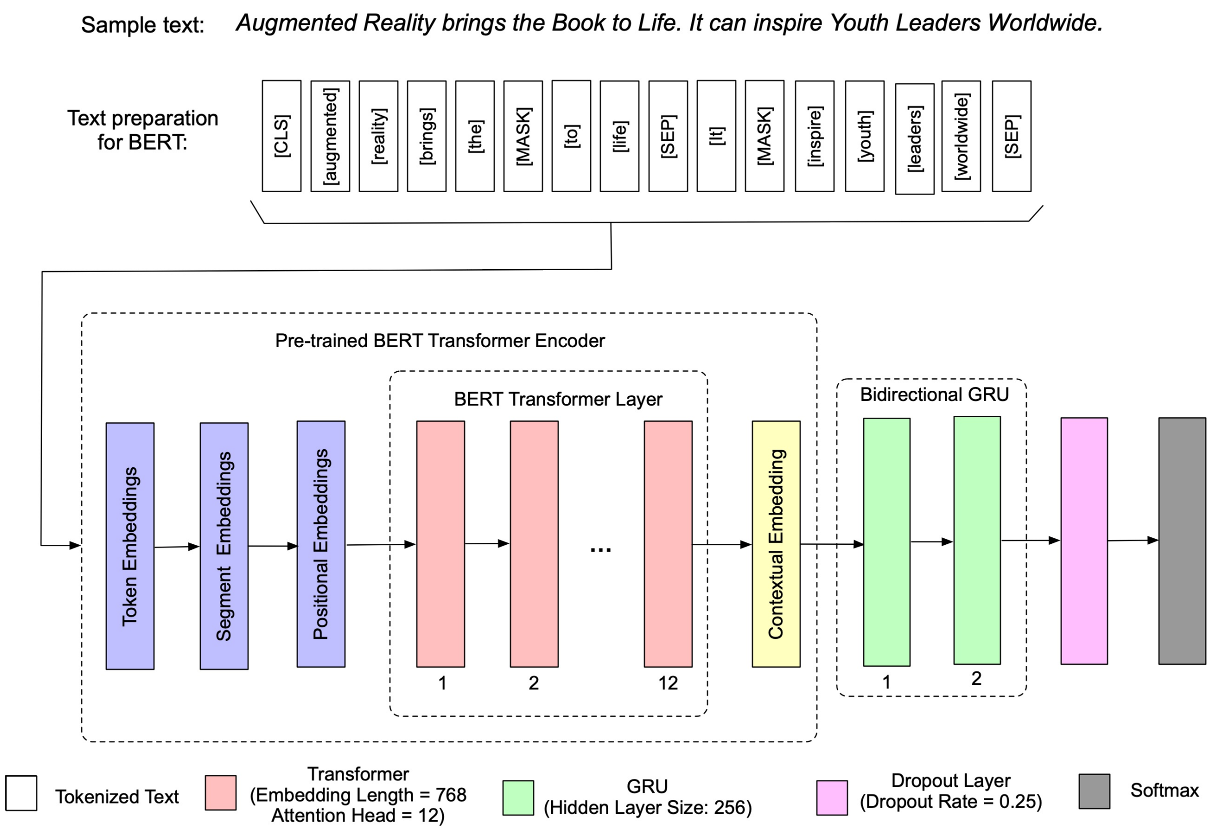

Fig. 3. Schematic diagram of sentiment analysis use in this research.

had to first be discarded. Next, a series of preprocessing techniques were implemented on the textual data using NLTK,[9] which included removing numbers, punctuation, inconsequential characters, converting letters to lowercase, tokenizing words, removing stop words, stemming, and lemmatization of words. However, hashtags from Twitter posts were retained to increase precision [1]. An overview of preprocessing procedures is shown in Figure 4. One extra step was taken to eliminate irrelevant data entries due to irregular language or abbreviations commonly used on social media, such as Twitter [78]. We add a pre-compiled stopwords list, such as "art", "latex", "textile", "cotton", and "brooch", for tweets which contained the keyword “wearable” was created, and it was discovered that about 11,444 tweets (1.83% of Twitter data) are not related to digital wearables, and thus were removed. For news media, academia, and entrepreneurship communities, we did not observe any irrelevant records, and our analysis revealed zero noise. The result will be a dictionary of words and a corpus which maps word id and word frequency for the LDA task. For example, (0,10) indicates the word with word-id 0 appears ten times in the first post.

3.5.2 LDA Hyperparameter Tuning. Perplexity was a parameter used in LDA to measure how well a probability distribution predicted a particular model. However, Chang et al. [19] illustrated that perplexity did not provide

[9]https://www.nltk.org/zs

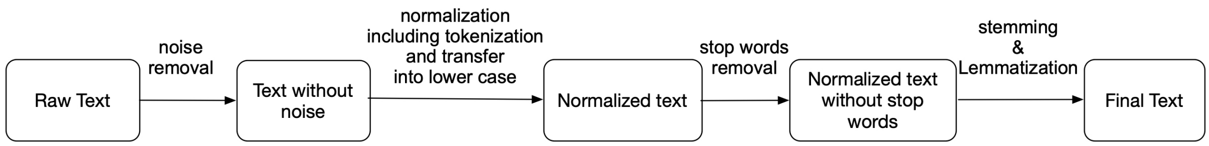

Fig. 4. Preprocessing procedures for sentiment analysis and LDA

sufficient support for exploratory goals in topic modeling. Therefore, as an alternative to perplexity in our LDA model, we employed a "coherence score" which measured the semantic similarities between high-frequency words in the topic. The coherence score featured strong correlations with human judgment [68]. We chose a specific measure of coherence score proposed by Röder et al. in 2015 [90]. In contrast to other measures, such as UMass Coherence [107] and UCI Coherence [72], C_v Coherence [90] combines co-occurrence word counts in a sliding window (window size of 110), using an indirect cosine similarity measure and normalized pointwise mutual information (NPMI).

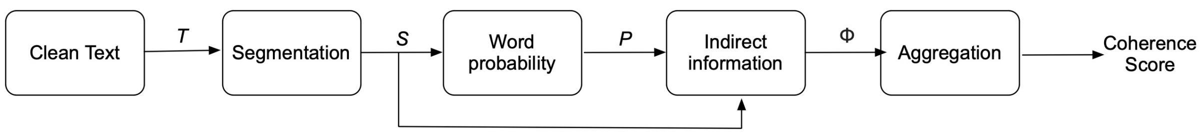

Fig. 5. Work flow of calculation of coherence score

The workflow of our coherence measure is shown in Figure 5. Firstly, input text T was segmented into a set of pairwise word subsets S. This means that each topic's top-N words are paired with every other topic's top-N words. For instance, let W be one of the topics' top-N words, $W = \{W_1, W_2 \ldots W_m\}$, m is the top-m words in W. Then, $W^{'} \in W$ is a word which is paired with every other word $W^* \in W$. For example, if $W = \{W_1, W_2, W_3\}$, one pairwise subset is $S = (W^{'} = w_1), (W^* = w_1, w_2, w_3)$. Next, we computed word probabilities $p(w_i)$ based on a boolean sliding window, which was built upon our textual data. In other words, $p(w_i)$ presents the number of documents in which w_i appears divided by the total number of documents. The C_v Coherence measurement comprises a boolean overlapping sliding window calculation, where the window moves one word at a time throughout the document each time. For instance, assume document d_1 contains the following words $\{w_1, w_2 \ldots w_m\}$. As the sliding window moves through the document, virtual documents like $d_1 = \{w_1, w_2 \ldots w_m\}$ and $d_2 = \{w_2, w_3 \ldots w_{m+1}\}$ are defined. Then, the word subsets and word probabilities $p(w_i)$ are all passed to an indirect confirmation measure using NPMI and cosine similarity. Finally, all confirmation measures ϕ were aggregated into a single value using the arithmetic mean, which served as the the coherence score; the higher the coherence score, the more accurate the topic extraction.

We performed a series of hyperparameter tuning and parameter sensitivity analysis manually to determine the following three hyperparameters which contributed to our coherence score: number of topics (K), document-topic density (α), and word-topic density (β).

We began by selecting the optimal number of topics, K. Following Wallach et al. [107], we set the test range of α and β from 0.01 to 1 with a step size of 0.3. We also tested the normalized asymmetric prior of $1/K$ topics and the default symmetric prior to α. Since β represents word-topic density, an asymmetric β will cause topics to be similar to the word contents of each topic. Hence, only symmetric β with the addition of a range 0.01 to 1 with a step of 0.3 were tested. Table 3 shows the coherence score for the number of topics based on the corpus that

Table 3. Coherence scores for different number of topics

. (Numbers in bold indicate optimal number of topics and corresponding coherence score with fixed α and β.)

# Topics	α	β	Coherence Score
6	0.01	0.01	**0.507**
11	0.01	0.01	0.5055
8	0.01	0.01	0.505
13	0.01	0.01	0.5007
7	0.01	0.01	0.4993
9	0.01	0.01	0.4984
12	0.01	0.01	0.4977
15	0.01	0.01	0.4967
5	0.01	0.01	0.4958
10	0.01	0.01	0.4944
14	0.01	0.01	0.4927

Table 4. Coherence score for different α and β

. (Numbers in bold indicate the optimal combination of hyperparameters.)

# Topics	α	β	Coherence Score
6	**0.01**	**0.01**	**0.507**
6	symmetric	0.91	0.5065
6	0.01	0.91	0.5060
6	0.31	0.31	0.5053
.	.	.	.
.	.	.	.
.	.	.	.
6	0.61	0.91	0.4818
6	0.61	symmetric	0.4796
6	0.61	0.31	0.4772
6	0.31	symmetric	0.4712

Table 5. Results of hyperparameter tuning. (Number in bold indicates lowest and highest improvement.)

Platform	Baseline Model	Fine-Tuning	Improvement	Optimal # Topics
Academia	0.2224	0.3254	**0.4632**	5
Entrepreneurship	0.3979	0.4626	**0.1627**	9
News media	0.4268	0.5070	0.1880	6
Social media	0.4138	0.4889	0.1815	14

was created for each data source. To maintain a constant sum of hyperparameters, which was recommended for Dirichlet hyperparameters [42], the values of α and β were fixed and set to equal 0.01 in Table 3.

After the optimal number of topics for each platform was identified, the α and β parameters were configured (see Table 3) based on the number of topics chosen in the previous step. Finally, the model was trained for each platform using the best hyperparameters that were identified (red values in Table 3 and Table 4).

Table 5 presents improvement over the baseline models following fine-tuning, plus the optimal number of topics for each platform. Its results are based on hyperparameter tuning results in Table 3 and Table 4. Academia datasets yielded the most improvement, at approximately 46% over the baseline model, while news media gained the least improvement, with a 16.3% gain compared to its baseline coherence score.

We trained our final models with the accurate combination of hyperparameters and distributed model results with the top 50 words for each topic across all platforms. Next, three researchers independently and manually labeled each topic based on their particular word lists. Their labeled topics featured almost perfect agreement based on Fleiss' kappa [36] (92%). The three researchers agreed on seven topics: "Brain-Computer Interface (BCI)", "Wrist-Worn", "XR", "Exoskeleton", "Smart Textiles", "Other Body Wearables", and "Consumer Market", which were the most common. Afterwards, they assigned each text to one or several of the topics. Some unanticipated topics were also observed during the labeling process, such as "Privacy and Security", "Fashion of Wearable Technology", and "Blockchain", however, a one-way ANOVA on the number of appearances of the topics was not significant in comparison to other groups (significance level of 0.05, P-value = 0.1038).

In the final step, topics with the same labels within the same platform were combined. In addition, a sub-label alongside the topics was created. For instance, "Training", "Entertainment", and "Fitness and Healthcare" were sub-labeled to clarify the purposes of individual posts within the topic. Labeled results was used as one of the features for our sentiment analysis; other features will be explained later (see Table 8).

Table 6. Results of training on IMDB

Epoch	Train Loss	Validation Loss	Train Accuracy	Validation Accuracy
1	0.4940	0.2910	0.7470	0.8820
2	0.2820	0.2280	0.8847	0.9096
3	0.2380	0.2250	0.9041	0.9121
4	0.2060	0.2290	0.9181	0.9154
5	0.1770	0.2340	0.9312	0.9158

3.5.3 BERT Sentiment Analysis. To use BERT for our sentiment analysis, we trained our model using the IMDB[10] (Large Movie Review Dataset v1.0), which provides over 25,000 binary (negative, positive) movie reviews. The best batch size and epoch sizes were identified using parameter sensitivity analysis, which are not reported here. Table 6 presents the training results. We chose parameters which gave us the best validation loss and tested them on the test set. The best test loss result was 0.205 and the accuracy was 91.81%. Afterwards, we employed these parameters for our final model and sent the preprocessed text through the final model for sentiment analysis.

The labeled topics obtained from our LDA model were our first features. Each individual post of the document, which can include more than one sentence, was computed and assigned a sentiment score. An average sentiment score was then calculated, which corresponded to each labeled topic.

To further analyze the particular attitude of each sector towards each wearable technology, we also computed average sentiment scores for each of the 36 keywords per platform (as shown in Table 7). To compare attitudes towards various products from different sectors, we performed a topic evolution analysis [111] of sentiments within and across different platforms.

4 RESULT

In this section, we present sentiment analysis results based on LDA topic modeling and the 36 listed keywords across all six platforms. Table 7 shows the sentiment score for each keyword in each platform. The sentiment scale spans from 0 to 1; the larger the number, the more positive the sentiment. For reference, a sentiment score of 0.5 indicates a neutral attitude.

4.1 News Media

The news media covers all 36 keywords identified in this study and consistently holds extremely positive attitudes toward "Consumer Market" through 2019. In particular, 2015 seems to be a "bull market" for wearable technologies, with most topics hitting their highest sentiment scores in that year and steadily declining until 2018. BCI records the most stable topic with sentiment scores around 0.75 until the start of 2020, which gets a sentiment score of 0.5829. News media appears to think highly of the "Healthcare" applications of wearable technologies, as they use an affirmative tone in discussing such wearable devices.

LDA topic modeling for the news media reveals nine topics (Figure 6). Of these, two of these topics were unanticipated by our three researchers who labeled the data and therefore, instead of seven topics, our LDA identified two more additional topics, "Privacy and Security" and "Fashion of Wearable Technology". "Consumer Market" posts comprise 8.5% of total posts, with a largely positive sentiment score of 0.842. Some other topics also share considerable positive sentiment over the years, such as "BCI" (41.6% of posts), "wrist-worn" (4.8% of posts), "XR" (14.6% of posts), and "Fashion of Wearable Technology" (7.3% of posts).

[10]http://ai.stanford.edu/~amaas/data/sentiment

Table 7. Sentiment score of keyword by sector.

(NA indicates that the target platform does not have sufficient information for a sentiment score of this keyword. Numbers in bold indicate lowest and highest sentiment within the sector.)

Keyword	News media	Entrepreneurship	Academia	Social Media
Augmented Reality	0.8845	0.9026	0.4585	0.6555
Body Gadget	0.7776	0.9649	NA	0.5598
Brain-Computer Interface	0.7392	NA	0.6170	0.5726
Body Robot	0.7353	0.8530	NA	**0.4827**
Digital Bracelet	0.9057	**0.9788**	NA	0.7029
Digital Cloth	0.8226	0.8884	NA	0.6724
Digital Goggles	0.8472	NA	NA	0.7045
Digital Necklace	0.8071	0.8571	NA	0.6839
Digital Prosthesis	0.8637	NA	NA	NA
Digital Ring	0.7858	0.9728	0.4444	0.6566
Digital Shoes	0.7981	0.9158	NA	0.6355
Edible Robot	**0.6681**	NA	0.5	0.5240
Exoskeleton	0.7143	0.8533	0.4457	0.5550
Fitness Tracker	0.8063	0.8536	0.4651	0.6485
Head Display	0.7726	NA	NA	0.5910
Head Wearable	0.7416	NA	NA	0.6212
Head-mounted Dsiplay	0.8072	NA	0.5988	0.5962
Intelligent Cloth	0.8440	**0.5515**	**0.7778**	0.5912
Mixed Reality	0.8477	0.9258	0.4545	0.6522
Smart Band	0.8911	0.8569	0.537	0.6579
Smart Bodywear	0.8223	NA	NA	NA
Smart Bracelet	0.8448	0.9126	0.5478	0.6810
Smart Clothes	0.8566	0.9399	0.5746	0.5596
Smart Glass	**0.9123**	0.9033	0.5452	0.6495
Smart Goggles	0.8464	0.9567	NA	0.6371
Smart Necklace	0.8823	0.9411	NA	0.6577
Smart Patch	0.7827	0.9194	0.5516	0.5672
Smart Prosthesis	0.8875	0.9072	0.4935	0.5324
Smart Ring	0.8979	0.9089	0.5337	0.6573
Smart Shoes	0.8782	0.8385	0.5341	0.5647
Smart Suit	0.8219	0.9299	0.5635	0.5787
Smart Tattoo	0.8056	NA	0.5337	0.57
Smartwatch	0.8700	0.8764	0.4797	**0.7157**
Virtual Reality	0.8875	0.8881	0.4572	0.6396
Wearable	0.8785	0.8979	0.4580	0.6393
Wrist Worn	0.8375	0.9464	**0.4404**	0.5637

We observed that news media holds an extremely active attitude towards "XR", "Smart Glass", and "Smart Goggle" (combined 5.3% of posts). Since our news media dataset contains posts from Google, we believe this is related to Google's policy to promote their own products, such as Google Cardboard and Google Glass. Following the discontinuation of Google Glass in early 2015, the enthusiasm toward "XR" on Google News waned [9, 89]. Google shifted its focus to business applications of XR glasses in mid-2017 [92], then again, the attitude toward "XR" gradually improved, as shown in the heat map in Figure 4. The same phenomenon was observed for topics including "wrist-worn" and "exoskeleton".

Another unique topic mentioned only in the news media was "Smart Textile" (3.4% of posts), which refers to digital artifacts which can be embedded in users' clothing. This topic also had a moderately positive sentiment score.

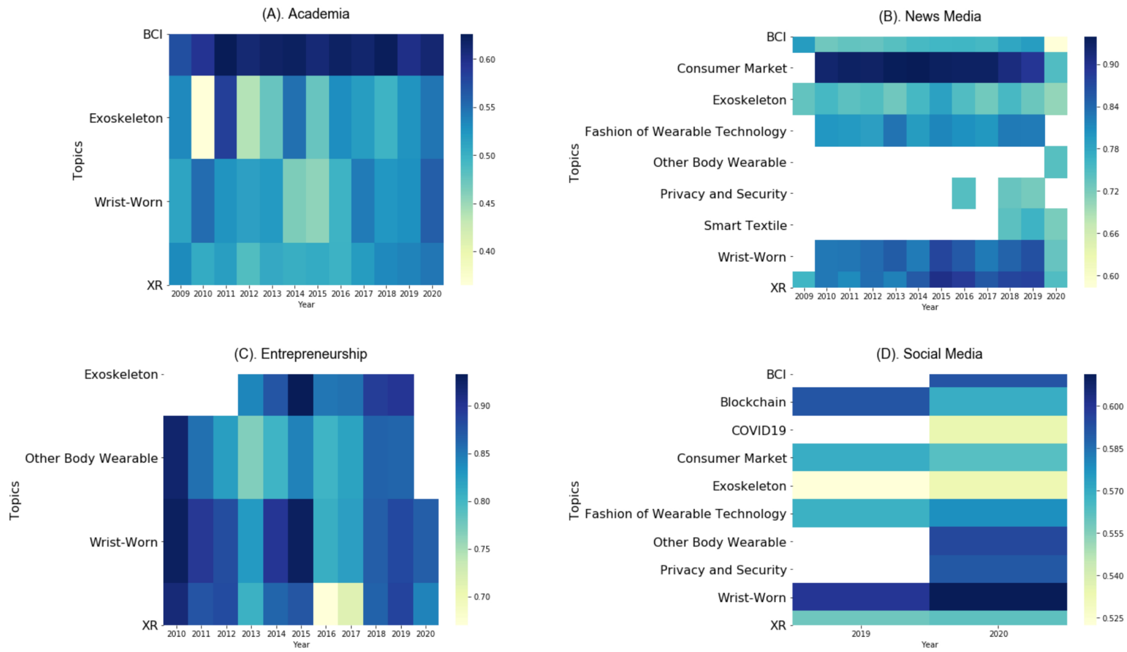

Fig. 6. Heat map of yearly sentiment scores for topics in four groups

On the other hand, "Privacy and Security" (4.9% of posts) recorded the lowest sentiment score (just over 0.7), however, its score still indicates a moderately positive attitude towards the problems that wearable technology products face. Though "Exoskeleton" (14.6% of posts) had a lower sentiment score than any other topics, the news media's attitude towards it was still positive, with a sentiment score of over 0.7. Since the topic "Other Body Wearable" (2.3% of posts) only appeared in our data from 2020, we can not make any judgement about it.

Based on the sentiment results shown in Table 7, the lowest sentiment score recorded was 0.6681, which belonged to "Edible Robot" (1.6% of the post). However, the number of posts referring to the "Edible Robot" keyword rose in recent years, indicating increasing interest in precision medicine and health care.

Although news media displayed overall positive attitudes towards most topics, it was not favorably disposed toward products designed for training purposes, such as "Virtual Personal Trainers" and "Interactive Training". The sentiment scores for these applications were significantly lower than compared to others. We believe this phenomenon originated from the risk of Artificial Intelligence taking over human jobs and resulting decrease of future jobs [49].

News media presented a significant reduction in sentiment scores in 2020. Two individuals manually analyzed articles from both Google and Bing news published in 2020, and discovered two reasons possibly underlying this change in sentiment. Firstly, the number of news stories regarding wearable technologies reduced from previous years due to the COVID-19 pandemic and the associated increase in news coverage of disease-related technological advancements. Secondly, at the time of writing this manuscript, only data for the first half of 2020 was available.

4.2 Entrepreneurship Community

To understand the sentiments of the entrepreneurship community, we employed data collected from Indiegogo and Kickstarter. Both datasets featured a large focus on "XR" and "Wrist-Worn" (80.8% of posts), which showed high market competition in these sectors. Referring to Table 7, almost every keyword gained an extremely positive sentiment score, with "Digital Bracelet" (another name for wrist-worn wearables) recording the highest sentiment (0.9788).

Furthermore, the entrepreneurship community featured sentiment scores greater than 0.9 for more than half of wearable technology keywords (Table 7). Taking into consideration the purpose of these two websites, these results are predictable given that many members of the community are promoting wearable products for financial profit. In particular, crowdfunding focuses on delivering innovative products and seeks to get funding from consumers.

In this sector, "Healthcare" products had the highest sentiment score among the three other categories ("Fitness", "Entertainment", and "Training"), while these three categories each performed equally well, with sentiment scores above 0.85.

On the other hand, "Intelligent Cloth" had a sentiment score of only 0.5515; however, this may be due to a lack of sufficient data entries for this product type, since it was mentioned in less than 1% of entrepreneurship community posts. Therefore, we omitted this keyword from our analyses.

"Other Body Wearable" (14.1% of posts) and "Exoskeleton" (5.1% of posts) were two other topics listed in the entrepreneurship community dataset. Unlike "Wrist-Worn" and "XR", which exhibited a remarkable sentiment drop from 2016 to 2017, the entrepreneurship community held relatively consistent attitudes towards "Other Body Wearable" and "Exoskeleton".

One topic that the entrepreneurship community did not cover, which was covered by the other three communities, was "BCI". Keywords related to "BCI", such as "Head Display" and "Head Wearable" mostly appeared in academia and news media.

We believe this type of wearable technology was not mature enough to be incorporated into daily life due to physiological and psychological concerns as well as technological and social concerns [10]. Therefore, more systematic research and experimental evaluations need to be done in this area [69].

Data for the entrepreneurship community from the first two quarters of 2020 was also collected. However, the impact of COVID-19 on this sector was substantial, as sufficient data could not be compiled to report any trends.

4.3 Academia

Academia ranged from slightly positive to negative towards all 36 keywords that were analyzed. In comparison to other communities, academia had a more confined interest in wearable technologies. The main keywords mentioned and discussed in this sector were "Brain-Computer Interface", "Exoskeleton", "Wrist-Worn", and "XR". Sentiment scores in this sector remained largely steady during several years of study, and sentiment scores for all fours topics ("brain-computer interface", "exoskeleton", "wrist-worn" and "XR") varying only slightly across the years surveyed. "BCI" performed slightly better than the other three topics, and it presented a sentiment score $\tilde{0}.6$ over most of the other years.

Instead of focusing on entertaining applications of wearable technology, academia was focused on how to improve or evaluate these technologies to assist and educate users. Only "Healthcare" oriented wearable technologies had a slightly positive sentiment score of 0.5259. Based on the sentiment scores for keywords in Table 7, there were some types of products, like "Smart Shoes", "Smart Band", and "Smart Bracelet", as well as the highest scoring product, "Intelligent Cloth", which academic researchers had largely positive attitudes towards. However, these categories made up less than 1% of the total dataset. The "Wrist-Worn" keyword had the lowest sentiment score in academia (0.4404), but text related to this topic only comprised less than 1% of the whole

Table 8. Sentiment scores regarding the purpose of wearable technology product.

(Numbers in bold indicate lowest and highest sentiment scores within the sector.)

	News media	Academia	Social Media	Entrepreneurship
Fitness	0.8216	0.4575	**0.5713**	0.8788
Entertainment	0.8583	NA	0.5864	0.8869
Healthcare	**0.8874**	**0.5259**	**0.6275**	**0.8956**
Training	**0.6567**	**0.4559**	0.5724	**0.8513**

dataset. As a result, meaningful conclusions about academia's views of these types of products could not be provided due to limited data availability and its statistically insignificant contribution to the dataset.

While offering the narrowest coverage of the wearable technology community in terms of keywords used to describe them, academia also had the lowest sentiment scores towards wearable technologies among all four sectors. It seems likely that this sector expresses a slightly positive, neutral, or negative attitude towards wearable topics because researchers write about wearable technologies in candid, precise, and non-emotional language. This does not necessarily mean that academia holds negative opinions of these useful technologies; instead, they analyze and evaluate its pros and cons objectively based on experimental data and without injecting subjective opinion.

4.4 Social Media

We chose Twitter as a representative social media platform for this study. As shown in Table 7, Twitter had a wide range of coverage of the 36 keywords. Overall, social media users' attitudes were between those of the news media and entrepreneurship community, and academia. Twitter users displayed a positive attitude about every type of wearable technology, ranging from slightly positive (e.g. "Brain-Computer Interface" (0.5726), "Smart Prosthesis" (0.5324), and "Exoskeleton" (0.5550)) to moderately positive (e.g. "Smart Watch" (0.7157) and "Digital Bracelet" (0.7029)), except for "Body Robot", for which there was a negative sentiment (0.4827).

According to the theory of perceived value, end-users tend to be more positive towards product types that they are more familiar with, such as "Smart Watch", "Smart Band", and "Augmented Reality". On the other hand, social media users find less perceived value for products that are the least common in their daily lives, such as "Edible Robot" and "Exoskeleton", leading to lower sentiment scores. We noted that wearable products which can easily incorporate both technological innovation and fashion character display significantly better sentiment scores (see Figure 6). For example, "Fashion of Wearable Technology" had a relatively moderate sentiment score (slightly greater than 0.56) among social media users.

Social media users mainly communicate about "XR" and "Wrist-Worn" (over 80% of the dataset) wearables in their posts, with relatively high sentiment scores (over 0.55). Products in these two categories were also the most common in the wearable technology market. In contrast, "Exoskeleton" performed relatively poorly among social media users throughout the years. Social media users were most likely to be interested in "Healthcare" oriented products, which Twitter users mentioned with a moderately positive tone (sentiment score of 0.6275). Compared between the three subfields, "Fitness" received the least positive sentiment, which may be due to inaccuracies of measurement [114]. "Consumer Market" was also mentioned in Twitter posts with an increasingly positive sentiment (see Table 8).

It is important to note that the topics of "Blockchain" and "COVID-19" have not yet been mentioned in any other platforms with regards to the discussion of wearable technologies. Even though they comprise a small proportion of the dataset, it is still useful to show that their appearance affects social media communications about wearable technologies.

5 FINDINGS AND DISCUSSION

In this section, we summarize the most important findings from our analysis and briefly discuss future directions, while acknowledging our research limitations.

Both the news media and entrepreneurship community displayed positive attitudes towards wearable technologies. However, social media and academia's views of wearables were less positive. Sentiment scores, by either keyword or topic, showed that the entrepreneurship community always expressed the most positive attitudes toward wearable technology out of the four fields surveyed. This positive result was in line with the purpose of these platforms, which both offer crowdfunding opportunities for developers and small businesses. Nevertheless, in our analyses, we discovered disparities in sentiment scores between Kickstarter and Indiegogo for specific product types. While Kickstarter was extremely positive regarding their products (average sentiment score of 0.9226), Indiegogo displayed less positivity (average sentiment score of 0.6736).

News media also projected a positive attitude towards wearable technology, especially news extracted from Google news. Delving deeper into different product types, news media recorded even higher sentiment scores than the entrepreneurship community for the keywords "Exoskeleton" and "Smart Band".

Although the entrepreneurship community and news media strongly praised wearable technologies, social media users showed less passion toward wearable technologies. Social media users displayed a moderately positive attitude toward "Healthcare" oriented wearable technologies (e.g. smartwatches, fitness trackers). On the other hand, they exhibited craving for some state-of-the-art products in the wearable technology market such as "Blockchain", a relatively new communication technology that can be fused into wearable applications.

XR was the most discussed technology across three out of four sectors. XR, the umbrella term for mixed reality, virtual reality, and augmented reality, was mentioned in almost 50% of posts analyzed from all sectors except news media. Furthermore, XR gained positive sentiment scores ranging from conservatively positive to extremely positive in three out of four sectors, excluding academia, which appeared to be critical of wearable technologies. The negative attitudes of academia demonstrate that wearable technology has not yet fully matured, and that its applications still have room for improvement specifically with regards to battery challenges [87] and issues with the quality of collected data [82].

BCI could achieve monumental success as a wearable technology, and it recently started to receive more attention. BCI has a wide range of usage, such as entertainment[37], clinical applications [63], and patient care[96]. Nevertheless, BCI-based applications are not widely accessible to end-user consumer markets, which can be observed from very few posts in social media covering this topic (less than 1% of posts). The entrepreneurship communities analyzed by our team display no interest in BCI products. On the other hand, news media holds consistently positive attitudes towards it, as well as academia, which maintained high sentiment scores towards BCI over the years. Although social media had very few posts regarding BCI, its sentiment score is relatively high among all other topics covered in social media. As the entrepreneurship community and academia continue to make this type of technology more accessible to the public, we estimate that BCI technologies will find their path into consumer markets.

There are several concerns among users related to the privacy and security of wearables. Privacy and security of wearables are mentioned by news media and social media and these concerns are found in the analysis of news media sentiments throughout the years. In the entrepreneurship community, these issues have also received poor sentiment scores. In line with previous research [115], we conclude that insufficient support for privacy and security have affected all sectors of wearable technologies. There are opportunities in the wearable technology market, and especially in the entrepreneurship community, to innovate and address these issues and concerns.

Fashion has a high potential in the wearable market. According to the results of our LDA topic modeling, 15% of news media and 14% of social media posts mentioned fashion design of wearable products. Each of these posts received relatively moderate sentiment scores, with inspiring tendencies to rise within their sectors. Based on these observations, we conclude that the consumer market not only wants a product with practicality, reliability, and functionality, they also demand a product which represents personality and style. By the same logic, attitudes of the news media seem to indicate that the design of wrist-worn products may cause a fashion-based wave of adoption of wearable products.

Wearable healthcare applications could lead the future development of the industry. Healthcare-oriented wearables appear and record positive sentiment scores in all four groups of datasets. There was a generally positive attitude toward the use of wearables for digital health. Meanwhile, wrist-worn and XR were the most mentioned topics across all four sectors. Due to the COVID-19 pandemic, wearable technologies may gain increased market share within the healthcare sector in the future. This pandemic exposed several loopholes in digital health [73] and demonstrated the potential for the community to use wearable technologies [40] to reduce health risks.

Unlike other platforms, social media users have the least interest in "Exoskeleton". As shown in Figure 6, news media posts began to mention "Exoskeleton" in 2009, with a moderately positive stance (0.7373 sentiment score). Academia had a less positive standpoint at the same time, with a consistently negative tone in the years since. Compared to the other two topics which appeared in academia ("Wrist-Worn" and "XR"), "Exoskeleton" is the least favored topic overall, and has even seen a decreasing trend in recent years. Conversely, the entrepreneurship community discussed "Exoskeleton" products in 2013, with consistently positive attitudes. In spite of the active promotion of the entrepreneurship community and news media, social media users appeared to be conservative about exoskeleton products, with this topic receiving the least interest among all wearable topics mentioned on Twitter.

The news media and entrepreneurship community's attitudes toward wearable technologies did not have a strong impact on public opinion. Even with the positive attitude of the entrepreneurship community and some sectors of news media, social media (in this case, representing public sentiment) did not overly sought after wearable technologies, at least in the last two years. Although the public exhibited positive sentiment scores about almost every product in the wearable technology industry, their attitudes towards these products were more conservative than those of the news media. Therefore, the news media does not appear to lead or sway the public's attitude toward wearable technologies.

A "hyped" wearable technology receives users' favor for about three years. As a fast-growing market, wearable technology displays characteristics of diversity and inclusiveness. Although news media promoted various wearable products in recent years, end-users (measured from social media) had limited acceptance. For instance, social media users are not very positive about the exoskeleton. The highest sentiment of the end-user community is the field of healthcare in recent years (Table 8). Based on the heat map, it is possible to offer an estimate of the lifetime of favor for XR products. News media were overwhelmingly positive about XR in a three-year period from 2014 to 2016. The great mass fervor has dampened since then, but gradually climbed again in 2019. The same trend applied for the entrepreneurship community: after the period of interest in XR in 2010, the community became relatively quiet for the next two years. However, from 2013 to 2015, the community broke the log-jam in the market and rebounded. After just three years of upsurge, the entrepreneurship community displayed reduced interest in XR thereafter. Current heat maps for news media and the entrepreneurship community both indicate an upward trend for two major categories in the wearable technology market, including "XR" and "Wrist-Worn". Their attitudes toward these categories were increasingly positive going into 2019. However, due to the COVID-19 pandemic and limited data entries, 2020 displayed a sudden drop in sentiment scores in most wearable technologies. The data for all of 2020, however, is incomplete, and thus, it is preferred to avoid a robust justification for this year.

Biomedical science (PubMed) and computer science (DBLP) both have similar levels of interest in wearable technologies. According to academic data from 2009 to 2020 in the fields of computer science and biomedical science, the overall number of publications in biomedical science which included our keywords was greater than in computer science. We found that these two fields of academia both focused on three major topics of the wearable technology industry, including XR, wrist-worn and exoskeleton (Figure 1). Since their focuses are similar, combined data from these subfields to obtain a trend chart (Figure 2) based on the three major topics studied in academia. There was an increasing trend in all three topics before 2020, with "Exoskeleton" being the least researched and "Wrist-Worn" passing "XR" to become the most investigated topic in academia in recent years. In the heatmap in Figure 6, wrist-worn displayed an increase in positive sentiment scores, while XR and exoskeleton exhibited decreased trends in recent years. Based on this observation, it is believed that wrist-worn wearables will become more attractive to the academic community in the future.

The COVID-19 pandemic changed public perspective of healthcare technologies and wearables may gain a new, more positive role among healthcare technologies as a result. Lack of testing ability and protective supplies remain challenges for frontline workers during the pandemic [43]. Previous research on wearable technology and personal protective equipment (PPE) [79] displayed that their combination has already widely been used to save lives, such as when applied by firefighters [60] and miners [18]. The widespread use of wearable technology and PPE suggests the joint incorporation of these tools for healthcare. For instance, wearable technologies can advance protection for healthcare workers by enhancing operational performance and efficiency by continuously monitoring user body temperature, blood oxygen levels, and heart rate [34]. It is worth researching whether wearable technology products can detect infections before any symptoms appear, such as by measuring respiratory behavior with a smart shirt. Such technology can be incorporated into research and practice to prevent or combat future pandemics.

5.1 Limitations

Our study includes five limitations. Firstly, COVID-19 significantly changed community attitudes toward wearable devices. Therefore, there is a need for post-Covid-19 studies on technological advances, especially on wearables. Secondly, we did not collect the entire data for 2020 and our data collection phase is finalized in August 2020. Thirdly, the Twitter dataset which was collected is limited to 2019 and 2020, which prevents our team from making inferences regarding public opinions prior to 2019. Nevertheless, this issue is common in multi-resource studies [67]. Another limitation to this study was regarding the combination of data from Indiegogo and Kickstarter to describe the entrepreneurship sector, as both platforms are crowdfunding websites and provide the same services. However, the separate platforms also have different policies and as well as accessibilities in a limited number of countries. Finally, we combined data for Google News and Bing News to comprise news media. As a result, this limited our study to English articles. Since there are wearable technologies in countries such as Japan, China, and Germany, but are not targeting international markets and thus their market is limited and fall out of our study, because we can not detect them in English news media.

6 CONCLUSIONS

This research reported the results different perspectives from social media, academia, news media, and the entrepreneurship community toward the rapid proliferation of wearable technologies over the last 11 years by analyzing textual data from Twitter, DBLP, PubMed, Bing News, Google News, Indiegogo, and Kickstarter. Through topic modeling, our results revealed that there were six major categories of wearable technologies, each of which focused on different subfields: healthcare, entertainment, training, fashion, etc. Sentiment analysis was performed to gain knowledge about different community attitudes towards wearable technologies. Average sentiment scores of 36 keywords were used to scrape collected texts, and six major production categories with diverse focuses across six platforms were computed using a neural network algorithm (BERT). Our analyses indicated that news media and the entrepreneurship community both held considerably positive views of wearable technologies as a whole, while the entrepreneurship community held extremely positive attitudes toward specific wearable categories. In contrast to the preference of wearable technologies seen among news media and the entrepreneurship community, academia held a more critical standpoint, with slightly negative or neutral scores for approximately each type of wearable technology. Social media posts, considered to represent the voice of the public, displayed less positive attitudes toward the wearables market than the news media and the entrepreneurship community. Ultimately, based on these results and taking into consideration the rapid development of artificial intelligence and miniaturized devices, we have made predictions based on our data about future trends of some wearable technologies.

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7 APPENDIX

We used a statistical inter-rater measure, Fleiss' kappa [36] to assess the reliability of agreement between three independent researchers when independently mapping the topic modeling results into six major categories. In contrast to other measures, like Cohen's kappa [22], which works for no more than two researchers, Fleiss' kappa allowed more than two individuals to rate our labels.

We used the social media topic modeling results as an example here, since social media contains the most data of the six platforms examined, and is thus most likely to cover all seven topics. Topics which do not fit into our six topic categories were removed from our Fleiss' kappa table. There were two topics that did not fit into the six major categories, and their removal left thirteen topics to be decided. The agreement table 9 is provided below.

We let N be the total number of topics which was already decided by our LDA hyperparameter tuning, n the number researchers who participate in this labeling process (in this case, 3), and k the number of categories into which topics were assigned (since we predefined six categories, $k = 6$ here). Last but not least, the topics were indexed by $i = \{1, \ldots, n\}$ and categories by $j = \{1, \ldots, n\}$, so n_{ij} will be the number of researchers who assigned i-th topic into j-th category. We first found p_j, which was calculated by the ratio of j-th category to all the assignments represented by $N \cdot n$; all ratios will sum to 1 (as shown in Equation 1),

Table 9. Fleiss' Kappa Agreement Table

n_{ij}	XR	Wrist-Worn	Exoskeleton	Smart Textile	Other Body Wearables	Consumer Market	p_i
Topic 1	0	0	0	0	0	3	1
Topic 2	0	0	0	0	0	3	1
Topic 3	0	0	3	0	0	0	1
Topic 4	3	0	0	0	0	0	1
Topic 5	0	3	0	0	0	0	1
Topic 6	2	0	0	0	0	1	0.333
Topic 7	0	3	0	0	0	0	1
Topic 8	3	0	0	0	0	0	1
Topic 9	0	3	0	0	0	0	1
Topic 10	0	0	0	0	3	0	1
Topic 11	0	0	0	0	0	3	1
Topic 12	3	0	0	0	0	0	1
Topic 13	0	0	0	3	0	0	1
p_j	0.282	0.231	0.077	0.077	0.077	0.256	

$$P_j = \frac{1}{Nn} \sum_{i=1}^{N} n_{ij}, 1 = \sum_{j=1}^{k} P_j \tag{1}$$

The error term is then calculated by:

$$P_e = \sum_{j=1}^{k} P_j^2 \tag{2}$$

P_i, which represents the proportion of researchers in agreement to the total number of researchers, is computed by:

$$P_i = \frac{1}{\mathrm{n(n-1)}} [\sum_{j=1}^{k} x_{ij}^2 - n] \tag{3}$$

Table 10. Interpretation of Strength of Agreement with Calculated κ

κ	Strength of Agreement
< 0	None
0.01–0.20	Poor
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Near-Perfect

The mean of P_i is therefore:

$$\overline{P} = \frac{1}{N\mathrm{n}(\mathrm{n}-1)}(\sum_{i=1}^{N}\sum_{j=1}^{k} n_{ij}^2 - Nn) \tag{4}$$

Fleiss' kappa is defined as

$$\kappa = \frac{\overline{\mathrm{P}} - \mathrm{P_e}}{1 - \mathrm{P_e}} \tag{5}$$

To investigate our kappa value, we followed the strength of agreement table proposed by Landis and Koch [59]. Based on the results, our example κ falls into the category of substantial agreement with a score of 0.947, indicating that our independent labeling is largely in agreement, allowing us to move forward with these labels. We applied this method to all six LDA topic modeling results; our level of agreement ranged from substantial to near-perfect agreement (Table 10). Thus, we proceeded by applying the labeling result with the most votes in each case. For topics which did not fit into the six major categories, three researchers collaborated to assign labels.