# DigiCall: A Benchmark for Measuring the Maturity of Digital Strategy through Company Earning Calls

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## Abstract

Digital transformation reinvents companies, their vision and strategy, organizational structure, processes, capabilities, culture, and enables the development of new or enhanced products and services delivered to customers more efficiently. By formalizing their digital strategy, organizations attempt to plan for their digital transformations and accelerate their company growth. Understanding how successful a company is in its digital transformation starts with accurately measuring its digital maturity levels. However, existing approaches to measuring organizations' digital strategy have inconsistent results, and also do not provide resources (data) for future research to improve. In order to measure the digital strategy maturity of companies and provide a benchmark, we leverage the state-of-the-art NLP models on unstructured data (earning call transcripts), and reach the state-of-the-art levels (94%) for this task. We release 3.691 earning call transcripts and also annotated data set labeled particularly for the digital strategy maturity by linguists.

## 1 Introduction

Digital transformation (DT) has emerged as an important phenomenon and is expected to preserve its prominence for companies. International Data Corporation (IDC, 2021) forecast that global spending on digital transformation will reach \$2.8 trillion by 2025 and to exceed \$10 trillion over a five-year period. DT redefines how companies operate and enhances connectivity, and inclusion worldwide. According to United Nations(Nations, 2019), AI-enabled frontier technologies are helping to save lives, diagnose diseases and increase life expectancy, while AI-enabled education by enabling virtual learning environments, opens up programs to students who would otherwise be excluded. DT, at a high level, encompasses the profound changes taking place in society and industries due to the adaptation of digital technologies, while at the organizational level, organizations by practicing strategies that do not only embrace the implications of digital transformation but also reach better operational performance (Vial, 2019).

Vial(Vial, 2019) explores 282 works on digital transformation in the Information Systems literature and develops a conceptual definition of DT as *'a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computation, communication, and connectivity technologies* (p.118). Organizations, by formalizing their digital strategy and leveraging their digital resources, plan for their DT (Bharadwaj et al., 2013; Al-Ali et al., 2020; Jackson, 2015; Freitas Junior et al., 2016). In order to measure and evaluate the digital strategy of firms, the status quo of a company's digital transformation, and the digital maturity level are measured(Thordsen et al., 2020; Kane et al., 2017).

In this research, our conceptual interest is centered on measuring the digital strategy maturity of firms. By considering this as a text classification task of earnings call transcripts, we leverage several transformer-based architectures for text classification, in addition to rule-based approaches. In the end we present our measure and release two data sets for future research[1].

## 2 Related Work

Digital transformation research is one of the most growing areas and has been studied by management scientists(Gurbaxani and Dunkle, 2019; Vial, 2019; Kane et al., 2017; Bharadwaj et al., 2013; Sebastian et al., 2020), economists (Acemoglu and Restrepo, 2019; Nagaraj and Reimers, 2021), engineers(Issa et al., 2018), computer scientists (Al-Ali et al., 2020), and social scientists (Hilbert, 2022; Shibuya, 2020) in the literature. Despite there are many studies investigating the implications or drivers of DT

[1] https://github.com/hpataci/DigiCall



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in different fields, our focus is limited to studies in management science, computer science, and their intersection.

In this research, we predict the maturity of the digital strategy of S&P 500 companies by leveraging transformer-based models with domain knowledge. The most similar work to ours (Al-Ali et al., 2020)'s that uses earning call transcripts but does not release any data. Therefore, we do not have chance to test our approach on their data. However, available earning calls data sets (Li et al., 2020; Qin and Yang, 2019) have limitations that make it infeasible to measure the digital strategy maturity of companies. Moreover, there is no task-specific annotated data set available in the area particularly to measure the digital strategy maturity of companies.

Every quarter the executive leadership of a public company holds an earnings call meeting with investors and analysts to inform them about the status of the company, including their major digital initiatives. An earning calls transcript has mainly three parts, the first part consists of the names of company call participants, the second part consists of the presentation session of company executives, and the third part consists of a question-and-answer session. Existing earning call transcripts data sets do not provide both sessions, but only provide the answers of the most spoken company executive in the Q&A session(Li et al., 2020). The executives might share more information during the first session than during the Q&A session. One of the other major issues with the existing data-sets is that they only share one company executive's sentences by discarding other company representatives' comments (Qin and Yang, 2019). Therefore, this would also yield inaccurate results leading to biased analysis when we attempt to learn about how companies are performing in their digital transformation. In this research, we release all sections of the earning call transcripts without any section removal.

Any public company has 4 (Q1, Q2, Q3, Q4) earning conference call meetings annually in the USA. However, existing data sets in the literature have missing transcripts for some of these meetings. Measuring digital strategy maturity with missing earning conference call transcripts would yield inaccurate results. Such that if we obtain Apple's digital maturity in Q1 and Q2 of 2018, any digital strategy maturity analysis of Apple would be biased given that Apple might have disclosed several accomplishments in Q3 and Q4 of 2018. Moreover, available data sets in the literature have missing data points for some companies and this might also lead to inconsistent results to measure digital strategy initiatives. Such that (Li et al., 2020) discloses 3443 earning call transcripts of 1213 companies (average 3 transcripts per company ), while (Qin and Yang, 2019) discloses 576 earning call transcripts of 280 companies (average 2 transcripts per company). Therefore, to our knowledge, our data set has one of the longest time windows for earning conference call transcripts with the lowest number of missing transcripts (average 7 transcripts per company).

| **Dataset** | **DigiCall** | **MAEC** | **Keith** | **Qin** |
|---|---|---|---|---|
| Duration | 2018/19 | 2015/18 | 2010/17 | 2017 |
| Companies | 469 | 1,213 | 642 | 280 |
| Instances | 3,691 | 3.443 | 12,285 | 576 |
| Data Av. | Yes | Yes | No | Yes |

Table 1: Comparisons of our earnings calls dataset and the existing public earnings call datasets

## 3 Problem Definition and Our Hypotheses

There are several research studies attempting to measure digital maturity in management science literature (Thordsen et al., 2020; Gurbaxani and Dunkle, 2019; Kane et al., 2017). However, among these studies, the only study that leverages transformer-based models is (Al-Ali et al., 2020)'s work, and therefore it is the most similar to ours. In their work (Al-Ali et al., 2020), that they identify two tasks; first, the prediction of the aspect of the digital strategy, and second, the prediction of the maturity of the digital strategy. For the first task, they disclose a dictionary of 350 terms in 17 topics to be used with the prediction task [2]. Any sentence *s1* contains a term for the aspect of digital strategy, they combine it with the preceding *s0* and subsequent *s2* sentence from the transcripts and feed the appended sentences *s0+s1+s2* into the model. *We hypothesize that appending s0 and s2 with s1* might increase the noise in the data. Therefore, we only process sentences containing aspect maturity terms *s1*, and drop *s0* and *s2*. In the second stage, they predict the maturity stage. If the digital initiative is being planned, it is labeled as *plan*, if the digital initiative is being developed or piloted, it is labeled as *pilot*, if the digital initiative is launched

[2]The list of these terms and topics is available in The Appendix

and making an active contribution to the business, it is labeled as *release*, if the digital initiative is being pioneered and making a significant business impact, it is labeled as *pioneer*. *We hypothesize that a digital initiative released or pioneered completed in the past.* Hence, these two labels are combined under the past label by considering the temporal orientation (Hasanuzzaman et al., 2016; Keith and Stent, 2019) (grammatical tenses); Plan as Future, Pilot as Present, and Release and Pioneer as Past.

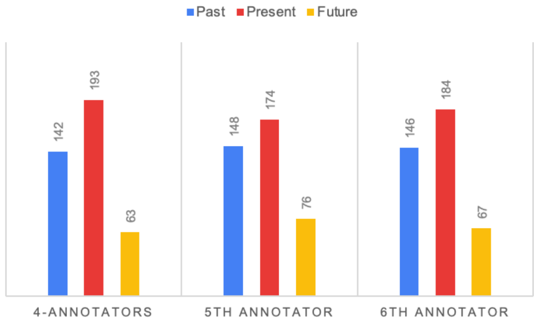


Figure 1: The Distribution of Annotations

## 4 Data Set Creation

### 4.1 Pre-Processing

Earning conference calls transcripts are recorded and shared as text and audio files by the company and third-party companies after each meeting. We collect earning conference call transcripts to measure the digital strategy maturity of the S&P 500 companies in 2018 and 2019 from Seeking Alpha. Each call document has mainly three parts, the first part consists of the names of company call participants, the second part consists of the presentation of company executives, and the third part consists of a question-and-answer section. We discarded the first section given that company executives' names have no impact on our task. [3] Despite the data was collected at the document level, we used Stanza (Qi et al., 2020)'s sentence tokenization to convert these documents into sentences and (Qi et al., 2020)'s Named-entity- recognition to remove questions, person's names, and this resulted with sentences of company executives. The baseline study in the area(Al-Ali et al., 2020) identifies two tasks; prediction of the aspect of the digital strategy, and prediction of the maturity of the digital strategy. They disclose a dictionary of 350 terms in 17 topics for the first task to be used with the prediction task. However, instead of considering the first task as a prediction task, we dropped the sentences that do not have matching terms with (Al-Ali et al., 2020)'s dictionary but kept if there is a match. In the second stage, we used the annotated data to fine-tune language models to predict the digital strategy maturity.

### 4.2 Annotation and Ethics

In order to annotate the pre-processed data, we instructed 4 freelancer linguists (2 Female, and 2 Male) from Upwork [4]. Each linguist at least had a bachelor's degree in linguistics, is a native-level English speaker, and at least has 95% positive feedback on Upwork. We randomly selected 400 sentences from 2018 data, distributed 100 sentences to each annotator, and compensated $40 to each annotator for this task and allocated one week. In the next stage, we instructed another linguist (5th person, Female), hired through Upwork with the same benchmarks and conditions, to agree or disagree with the annotated data by four people. The Cohen's kappa between the first 4-annotators and the 5th annotator is 84%. Finally, we instructed a 6th person (Male) with industry and domain experience, to agree or disagree with the annotated data by four people. The Cohen's kappa between the first 4-annotators and the 6th annotator is 95%, and between the 5th and 6th annotator is 88%.

## 5 Approaches

In this section, we provide details of different approaches applied for our task. For each following approach, the input is a textual string, i.e. a sentence from an earning call document, and the output is a label indicating the status of a company/a project. We consider three labels: *past*, *present* and *future*.

### 5.1 Part of Speech

The first approach is based on part-of-speech (POS). Given a sentence, POS tags provide grammatical information for individual words in the sentence. We use off-the-shelf tools to analyze each given sentence and use the output POS tags to determine the status of the sentence.

[3] We obtained the consent of Seeking Alpha to share the earning calls transcripts data on April 28, 2022. We thank them for their consent and acknowledgment. wwww.seekingalpha.com

[4] www.upwork.com

### 5.2 Language Models

Pre-trained language models have shown the state-of-the-art performance on various NLP tasks. We also fine-tune the pre-trained models for our task [5].

#### 5.2.1 Domain-Agnostic

We first consider following models pre-trained on general corpus. **BERT**(Devlin et al., 2018): One of the commonly used models that is pre-trained with different novel tasks such as masked language modeling, and next sentence prediction. Similar to other fine-tuning tasks, we simply use the BERT tokenizer to tokenize the sentence and use the pre-trained model to encode the tokenized sentences. **ALBERT**(Lan et al., 2019): A model based on BERT but has different architectures that save more parameters. **RoBERTa**(Liu et al., 2019): It is also a variant of BERT. The main difference between RoBERTa and BERT is that RoBERTa uses different masking strategies during pre-training and provides more robust performance.

#### 5.2.2 Domain-Specific

Different from previous models, we also consider models that are pre-trained on financial data as our task is based on financial documents. More specifically, we use another BERT-based model FinBERT(Araci, 2019). Based on the pre-trained BERT, FinBERT is further pre-trained on financial documents which demonstrates better performance on financial tasks. [6]

## 6 Experimental Evaluation and Findings

By building on previous work (Al-Ali et al., 2020) and several transformer-based models, we considered predicting the aspect maturity of the organizations' digital strategy as a text classification task with *past*, *present*, and *future* as labels. Consistent with the baseline study in the area (Al-Ali et al., 2020), we trained several domain-agnostic transformer-based models by applying fine-tuning with domain-specific data annotated by 4 different linguists. Despite RoBERTa provides the highest F-1 weighted at (Al-Ali et al., 2020)'s work, our findings show that BERT*base-uncased* provides the highest F1-weighted level (94%) while (Al-Ali et al., 2020) (58.2%). Given that we have different number of labels, and did not experiment with (Al-Ali et al., 2020)'s data, we are extending and adding to the literature by addressing some of the potential data issues in prior work. Different than previous work(Al-Ali et al., 2020), we experimented with a domain-specific model FinBERT (Araci, 2019). However, despite FinBERT being pre-trained and fine-tuned with finance domain-specific corpus it results lower F1-weighted. The rule-based approach, POS, provides the highest accuracy to predict the *Past* label.

| Model | F1 | Past Acc | Present Acc | Future Acc |
|---|---|---|---|---|
| **Rule-based** | | | | |
| POS | 0.91 | 0.92 | 0.88 | 0.88 |
| **Domain-agnostic** | | | | |
| BERT *base-cased* | 0.91 | 0.87 | 0.88 | 0.92 |
| BERT *base-uncased* | **0.94** | **0.88** | **0.98** | **0.92** |
| ALBERT *base-v2* | 0.89 | 0.84 | 0.87 | 0.92 |
| RoBERTa *base* | 0.79 | 0.79 | 0.86 | 0.75 |
| **Domain-specific** | | | | |
| FinBERT | 0.90 | **0.91** | 0.91 | 0.83 |

Table 2: Performance of the Proposed Models

## 7 Conclusions and Future Work

Predicting the maturity of the digital strategy of firms accurately might help researchers to explore organizations' digital transformation while providing insights on how to plan for digital transformation for organizations.

In our supplementary analysis, we find that industrial trends with respect to the maturity of the digital strategy also change with time, such that organizations disclose more past and future digital strategies in Q4 than in any other quarter. Future research might consider the time-variant factors that influence companies' digital strategy maturity. Such as, exogenous shocks, competitors' product releases might impact organizations' digital transformation. With the new proposed approach, it might be possible to predict which future digital strategy plans of organizations were suspended or accelerated by also considering the competitive behavior of organizations.

[5] In all transformer-based models, we randomly split the data as train, validation, test into 75%*75%, 75%*25%, and 25% respectively. All experiments were conducted at Google Colab Pro and randomly assigned to NVIDIA Tesla P100-PCIE (16GB) for GPU, and had the following settings: the learning rate 1e-5 (AdamW), epochs 6, batch size 3. We used the HuggingFace library https://huggingface.co/ for all models.

[6] https://huggingface.co/yiyanghkust/finbert-tone

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## Appendix

### Digital Strategy Aspect

This list presents 17 topics of interest detailed by 350 definitional terms obtained from (Al-Ali et al., 2020)

| Topic | Keyword | Keyword terms |
|---|---|---|
| Digital Technology | AI | \bAI\b, artificial intelligence, NLP, natural language processing, natural language understanding, NLU, natural language generation, NLG, speech recognition, sentiment analysis, speech to text, text to speech, deep learning, machine learning, \bML\b, neural network, algorithm, generative adversarial network, GANs, supervised learning, unsupervised learning, reinforcement learning, semi-supervised learning, active learning, self learning, transfer learning, back propogation, tensorflow, Salesforce Einstein, IBM Watson, kaggle, AI as a service, Microsoft azure ML, AutoML, autonomous vehicles, computer vision, image recognition, pattern recognition, cognitive computing, predictive analytics, predictive maintenance, algorithmic trading, clustering, dimensionality reduction, t-sne, PCA, principal component analysis, chatbot, \bbot\b, RPA, robotic process automation, matrix factorization, collaborative filtering, recommender system, recommendation engine, graph mining, graph theory, cortana, alexa, google assistant |
| | Cloud computing | cloud computing, cloud native, cloudless, distributed cloud, distributed computing, clustered computing, hybrid cloud, platform as a service, edge computing, cloud api, google cloud, azure cloud, aws cloud, software as a service, cloud applications, cloud, GPU, HPC management, cloud storage, elasticity, elastic computing, the cloud, data platform |
| | IoT | Internet of things, \bIoT\b, industrial internet, IIoT, embedded device, embedded sensor, digital twin, digital thread, building information modelling, BIM, connected devices, connected sensors, IoE, internet of everything, smart machines, connected machines, wearable, cyber physical systems, machine to machine, connected factory, model based definition |
| | Virtual reality | \bVR\b, virtual reality, immersive technologies, mixed reality |
| | Augmented reality | \bAR\b, augmented reality, immersive technologies, mixed reality |
| | Robotics | robots, humanoid, drone, drones, smart robots, smart warehouse, smart spaces, Lidar, computer vision, UAV, autonomous vehicles, swarm robots, industrial robot, robotics, automation |
| | Analytics | analytics, business intelligence, optimization, exploratory data analysis, data science, augmented analytics, descriptive analytics, descriptive statistics, prescriptive analytics, predictive, inference, inferential, customer segmentation, correlation, data visualization, data storytelling, text analytics, data lake, data warehouse, big data, social analytics, , network analytics, network mining, network analysis |
| | Mobile | mobile, smart phone, mobile app, mobile application, mobile platform, mobile solution, mobile technology |
| | Social | social media, social network, content marketing |
| | 3D printing | 3D print[a-z]*, additive manufacturing, 3D scan, material jetting, stereolithography, bioprint, bioprinted organ, Fused deposition modeling, Digital Light Processing, Selective Laser Sintering, Selective laser melting, Laminated object manufacturing, Digital Beam Melting |
| | Blockchain | blockchain, distributed ledger, decentralized, smart contracts, cryptocurrency, \bICO\b, initial coin offering, asset tokenization |

Figure 2: Digital Strategy as Aspect: obtained from (Al-Ali et al., 2020)

| Topic | Keyword | Keyword terms |
|---|---|---|
| Business Value | Digital Product | smart product*, connected product*, software as a service, Saas, platform as a service, Paas, platform, product as a service |
| | Digital Customer Experience | digital experience, customer experience, CX, user experience, UX, user journey, customer journey, digital engagement, customer engagement, personalization, personalisation, digital marketing, recommendation, market place, marketplace, e-commerce platform, digital service, digital services, e-service, online chat, chatbot, \bapp\b, digital chnnel, omnichannel |
| | Digital Operations | process automation, process mining, process analytics, process optimization, efficiency, cost saving, cost reduction, reduce cost, reducing cost, automation, predictive maintenance, ERP, supply chain, logistics, operations |
| | Digital Business Model | business model, new market, new segment, monitization, Saas, software as a service, on-demand, product as a service, value proposition, freemium, subscription, marketplace, ad-revenue, ads, peer-to-peer, two-sided, double-sided |
| Strategy Management | Enablers | digital strategy, digital business strategy, digital transformation strategy, governance, priositization, prioritization, digital vision, digital leadership, leadership support, leadership buy-in, communication, digital goals, data scientist, data analyst machine learning engineer, developer, coder, programmer, chief digital officer, CDO, head of digital transformation, head of digital, product manager, product owner, cross-functional, scrum master, agile coach, innovation manager, Data lake, data warehouse, middle ware, enterprise architecture, digital tools, digital workplace, digital integration, chat, video call, CRM, ERP, service oriented architecture, \bSOA\b |
| | Practices | Agile, scrum, MVP, minimum viable product, sprint, design thinking, business experiment, DevOps, \bepic\b, feature, user story, product owner, product manager, collaboration, cross functional, cross-functional, A/B testing, exploratory data analysis, data analysis, decision support system, dashboard, hypothesis testing, experimental design, product metrics, user metrics, usage metrics, click through rate, conversion rate, click stream, digital marketing, customer segmentation, risk modelling, simulation, decision analytics, decision support system, project management, digital skills, digital leadership, transformation, data analysis, social media management, social listening, user research, UX research, UX design, UI design, programming, coding, lean startup, experimentation, incubator, accelerator, innovation lab, digital lab, digital transformation, open innovation, design thinking, design sprint, digitalization, digitalisation, digitization, digital technolog[a-z]* |

Figure 3: Digital Strategy as Aspect: obtained from (Al-Ali et al., 2020): *continued*

## DigiCall's Contribution

### 1. DigiCall's contribution as a dataset

| | Number of Sentences with Digital Strategy Related Words based on Al-Ali et al., 2020'work | |
|---|---|---|
| | **DigiCall Data set** | **MAEC (Li et al., 2020)** |
| Twitter 2016 Q4 | #Past Digital: 8<br>#Present Digital: 18<br>#Future Digital:0 | #Past Digital: 1<br>#Present Digital: 8<br>#Future Digital: 0 |

We first extracted Twitter's Q4 2016 transcript document from the MAEC paper. We also obtained Twitter Q4 2016 transcript in a way that each earning call transcript is collected at the DigiCall Data set. We used our proposed approach to extract digital strategy-related keywords based on Al-Ali et al., 2020's dictionary, from both transcripts (MAEC and DigiCall's). Later, we used the pre-trained model to predict the maturity label for each sentence.

| | **MAEC** | **DigiCall** | **Sentence** | **Technology** | **Categories** | **Label** |
|---|---|---|---|---|---|---|
| 1 | **YES** | **YES** | The other thing that we're investing a lot in is making sure that we apply machine learning more broadly around our entire experience. | ['machine learning'] | ['AI'] | Present |
| 2 | **YES** | **YES** | We recently hired to consolidate all of our science efforts, all of our deep learning, all of our machine learning and artificial intelligence, so that we can get a lot smarter and provide more magical experiences for people around showing them what's breaking in real time and giving them a sense of what's going on without having to do as much work as they currently have to do on the platform. | ['machine learning'] | ['AI'] | Past |
| 3 | NO | **YES** | It's more what you have seen in the platform in sports, news, and entertainment and more globally. | ['platform'] | ['Digital Product'] | Present |
| 4 | NO | **YES** | One of the things that we've been very critical of Twitter on over the last several years is that it's been more of a passive platform where people have just been kind of reading almost RSS like, and my sense is over the course of the last couple of months or last six months, that you've seen an improvement in people actually engaging, whether that's actually tweeting themselves or liking or retweeting. | ['platform'] | ['Digital Product'] | Present |
| 5 | NO | **YES** | So to get double-digit growth for an entire quarter in impressions for three quarters in a row, it takes a fundamental change and that's being driven by machine learning in the timeline. | ['machine learning'] | ['AI'] | Present |
| 6 | **YES** | **YES** | And then the final point I'd make, which is somewhat tied to organizational decisions as opposed to execution or marketplace decisions, is that we are taking a step back and looking to simplify our product and putting our resources behind those products that we think have the greatest probability of success, that can deliver the best long-term growth potential, and that frankly leverage our competitive advantages in a unique way. | ['marketplace'] | ['Digital Customer Experience', 'Digital Business Model'] | Present |
| 7 | NO | **YES** | So hopefully that gives you perspective on the marketplace factors that are impacting our outlook. | ['marketplace'] | ['Digital Customer Experience', 'Digital Business Model'] | Present |
| 8 | NO | **YES** | We obviously want to build on that in 2017, and it's one part of our broader strategy to drive greater engagement of those that are already on our platform and to attract new users to the platforms. | ['platform'] | ['Digital Product'] | Present |

Figure 4: Sentences Containing Digital Strategy Initiatives DigiCall vs MAEC

| | | | | | | |
|---|---|---|---|---|---|---|
| 9 | NO | **YES** | The percentage of the audience that was less than 25 years old was 50%, in addition to the fact that a majority of the people that consumed the product were not in front of televisions and they only consumed it on mobile applications. | ['mobile'] | ['Mobile'] | Past |
| 10 | NO | **YES** | And then finally for our partners CBS and NBC and our advertising partners, we're able to leverage our innovation on mid-roll advertising that used dynamic ad insertion to mobile devices, to over-the-top applications and to the desktop web, which is a great innovation and allowed us to deliver specific ads to specific individuals from specific advertisers all at the same time. | ['ads', 'mobile'] | ['Mobile', 'Digital Business Model'] | Present |
| 11 | NO | **YES** | Those ads had 95% completion rates with sound on which is very attractive for advertising partners and obviously can result in high CPMs. | ['ads'] | ['Digital Business Model'] | Past |
| 12 | NO | **YES** | The first products that we developed on the platform were really organic products. | ['platform'] | ['Digital Product'] | Past |
| 13 | NO | **YES** | We had 600 hours of live video content programming on the platform in Q4, and it was pretty diverse: about 50% in sports, about 40% in news and politics and 10% in live. | ['programming', 'platform'] | ['Practices', 'Digital Product'] | Past |
| 14 | NO | **YES** | And then we've been consolidating organizations to build our strength, most notably in our machine learning and artificial intelligence efforts, which is critical to us being able to move much faster. | ['machine learning', 'artificial intelligence'] | ['AI'] | Present |
| 15 | NO | **YES** | Now just doing the work to get everyone on the same page and make sure that we have a platform internally that every team can use to provide better and more magical experiences on Twitter through machine learning and artificial intelligence. | ['machine learning', 'platform'] | ['Digital Product', 'AI'] | Past |
| 16 | **YES** | **YES** | And this focus and this team allows me and gives me a lot of confidence that I can continue to focus on the most meaningful things at both companies and we have the right prioritization in front of us. | ['prioritization'] | ['Enablers'] | Present |
| 17 | NO | **YES** | On your first question what I would say is that the President's use of Twitter has broadened the awareness of how the platform can be used and it shows the power of Twitter. | ['platform'] | ['Digital Product'] | Present |
| 19 | **YES** | **YES** | So at a macro level discussion on the platform really helps us be the best at showing what's happening in the world and more discussions strengthens our key differentiators in comprehensive and fast. | ['platform'] | ['Digital Product'] | Present |
| 19 | **YES** | **YES** | As it relates to impressions growth, which is another area we look at, as I mentioned earlier, the magnitude of the impressions of the platform is so large, it'd be very hard for an event or a single person to drive sustained growth in impressions growth. | ['platform'] | ['Digital Product'] | Present |
| 20 | NO | **YES** | February is a time period that historically has been up 35% to 40% versus January, and that ramp really starts in mid-January through February and that's when we saw more marketplace challenges in our ability to attract demand from advertisers. | ['marketplace'] | ['Digital Customer Experience', 'Digital Business Model'] | Present |
| 21 | NO | **YES** | And then kind of more of a philosophical partnership question, in the early days of Twitter you worked aggressively to extend the tweet footprint through partnerships with media companies, and I guess from a perspective of distributing tweet content, and I'm just wondering in light of the election and 's use of Twitter, do you look back at that strategy and then just wonder if maybe that you provide a disincentive for users to actually explore the platform if they feel like they are consuming a lot of those tweet content through media partners instead. | ['platform'] | ['Digital Product'] | Past |

Figure 5: Sentences Containing Digital Strategy Initiatives DigiCall vs MAEC

| | | | | | | |
|---|---|---|---|---|---|---|
| 22 | NO | **YES** | And so we really want to find these products that have multiple benefits, not just revenue but also content, and then also driving virality on the platform and faster distribution. | ['platform'] | ['Digital Product'] | Present |
| 23 | **YES** | **YES** | And we've now moved into a product area where we have a marketplace where content owners can put the content into the marketplace and advertisers can pick that content and not only put an ad in front of it but promote it. | ['marketplace'] | ['Digital Customer Experience', 'Digital Business Model'] | Present |
| 24 | NO | **YES** | They showed a real commitment post transaction to the developer community, and that was a really important element in our decision on where the product went in addition to maximizing shareholder value. | ['developer'] | ['Enablers'] | Past |
| 25 | **YES** | **YES** | So everything that we're doing around live streaming premium video within the app and also with individual-created, live-streaming video in Periscope has been the majority of our focus and we wanted to cut everything that did not go against that and did not matter. | ['app'] | ['Digital Customer Experience' ] | Present |
| 26 | **YES** | **YES** | And that's why I am excited about really making sure that we apply artificial intelligence and machine learning in the right ways and that we really meet that superpower of being that little bird that told you something that you couldn't find anywhere else. | ['machine learning', 'artificial intelligence'] | ['AI'] | Present |

## 2. DigiCall's Contribution as an Approach

| | **Example: Twitter 2016 Q4** | | | |
|---|---|---|---|---|
| | **Sentence with its original sequence** | **Technology** | **Category** | **Maturity** |
| S0 | So we're looking at all the patterns that we've seen for the past 10 years on how people use Twitter and to create experiences around that that make it easier to share what's happening, to talk about what's happening and to see it much faster. | [] | [] | Present |
| S1 | The other thing that we're investing a lot in is making sure that we apply machine learning more broadly around our entire experience. | ['machine learning'] | ['AI'] | Present |
| S2 | We recently hired to consolidate all of our science efforts, all of our deep learning, all of our machine learning and artificial intelligence, so that we can get a lot smarter and provide more magical experiences for people around showing them what's breaking in real time and giving them a sense of what's going on without having to do as much work as they currently have to do on the platform. | ['machine learning'] | ['AI'] | Past |
| S3 | So we're looking at a lot of opportunities to organize all the tweets around relevance but also around the topics and the interest and the passions that people care about. | [] | [] | Present |

<table>
<tr><th></th><th>Al- Ali et al. (2020)'s approach</th><th>DigiCall's approach</th></tr>
<tr><td>Approach</td><td>For any given sentence containing information about Digital Strategy initiatives (s1), combined with the previous (s0) and subsequent (s2) sentences.<br>So: s0+s1+s2 are processed to predict the maturity of the digital strategy.</td><td>Only considers the sentence (s1) with information about Digital Strategy.<br><br>So: s1 is processed to predict the maturity of the digital strategy.</td></tr>
<tr><td>Applied at Twitter 2016 Q4</td><td>S0(Present) + S1 (Present) +S2(Past)<br>Despite these three sentences containing different maturity levels, Al-Ali et al. (2020)'s approach would append these, and label them as Present (S1).</td><td>S0: would be discarded because no technology was disclosed.<br>S1: Present,<br>S2: Past.</td></tr>
<tr><td rowspan="2">Maturity Prediction: F-1 Weighted</td><td>BERT $_{\text{(base)}}$: 55.7 %</td><td>BERT $_{\text{(base)}}$: 94 %</td></tr>
<tr><td>RoBERTa $_{\text{(base)}}$: 58.2 %</td><td>RoBERTa $_{\text{(base)}}$: 79%</td></tr>
<tr><td>Label Level F-1 Weighted</td><td>Not Available</td><td>BERT $_{\text{(base)}}$: Past: 88% | Present: 98% | Future: 92%<br>RoBERTa $_{\text{(base)}}$: Past: 79% | Present: 86% | Future:75%</td></tr>
</table>

Figure 6: DigiCall's Contribution as An Approach