Date of Presentation ICRI 2023 Fall Convention

### How Artificial Intelligence Can Assist in Concrete Building Repair and Maintenance





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The ideas expressed in this ICRI hosted webinar are those of the speakers and do not necessarily reflect the views and opinions of ICRI, its Board, committees, or sponsors.

### OUTLINE

- Introduction
- Background
- Definitions of artificial intelligence (AI) and machine learning (ML)
- Potential application of AI/ML for asset management
- Potential application of AI/ML for health monitoring
- Conclusions



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### DAMAGE IN BULDINGS



CONCRETE REPAIR Restore | Repurpose | Renew YEAR ANNIVERSARY

### DAMAGE IN BULDINGS





### BUILDINGS RIGGED WITH SCAFFOLDING





### UNFORESEEN NATURE OF CONCRETE REAPIR



CONCRETE REPAIR Restore | Repurpose | Renew YEAR ANNIVERSARY





### **DELAYS!!**

### **LACK OF FUNDS!**



# EXCEEDINGLY DETERIORATED STRUCTURES LEADS TO HIGH REPAIR COSTS AND LOSS OF LIFE.

# THIS CAN BE PREVENTED BY REGULAR INSPECTION AND MAINTENANCE OF THE STRUCTURE.



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### **ARTIFICIAL INTELLIGENCE (AI)**

ARTIFICIAL INTELLIGENCE Programs that mimic human brain's ability to learn and reason "What a typical person can do in a timely manner based on previous experience, AI can probably do it."



## MACHINE LEARNING (ML)

"Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed."

### ARTIFICIAL INTELLIGENCE Programs with the ability to learn and reason like humans

### **MACHINE LEARNING**





### **DEEP LEARNING**



# **Regression models**



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# **Classification models**





# **AI/ML Process**



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### **Example of Florida bridge inventory**

#### Florida Bridge Information

th YEAR ANNIVERSARY

DISTRICT	COUNTY	OWNER	BRIDGE	STRUCTURE NAME	ROADWAY	ADT	FACILITY CROSSED	YI BU	EAR UILT REC	ONSTRUCTED	LAST INSPECTION	SUFFICIENCY RATING	HEALTH INDEX	NBI RATING
Central Florida	Brevard	State Highway Agency	700002	SR-405 WB - FECRR	SR-405 WB	7,550	FECRR		1969		11/9/2021	80.3	98.26	
Central Florida	Brevard	State Highway Agency	700003	3-7x4x110 CBC	US-1	15,236	Kid)Creek		1964		4/3/2020	69	58.85	
Central Florida	Brevard	State Highway Agency	700006	US-1 - Crane Cr. & City St	US-1	37,000	City St. & Crane Creek		1959	1990	10/22/2021	65	94.61	FO
Central Florida	Brevard	State Highway Agency	700007	US-1 over Elbow Creek	US-1	49,000	Elbow Creek		1961	1990	11/4/2021	92.3	93.96	
Central Florida	Brevard	State Highway Agency	700008	US-1- Eau Gallie River	US-1	54,000	Eau Gallie River		1961	1990	11/3/2021	85	95.22	
Central Florida	Brevard	State Highway Agency	700012	US-1 - FECRR	US-1	19,700	FECRR		1936	1961	9/13/2021	91.9	99.77	
Central Florida	Brevard	State Highway Agency	700013	SR-50 WB - St Johns River	SR-50 WB	6,100	St. Johns River		1971		12/15/2021	88.5	86.88	
Central Florida	Brevard	State Highway Agency	700014	SR-528 WB - US-1 & FECRR	SR-528 WB	20,000	US-1 & FECRR		1963	1970	10/27/2021	76.8	98.71	FO
Central Florida	Brevard	State Highway Agency	700015	SR-528 WB - CR-515	SR-528 WB	21,579	CR-515 & Indian River		1963	2001	10/28/2021	78.7	91.53	
Central Florida	Brevard	State Highway Agency	700017	SR-528 WB over SR-3	SR-528	15,250	SR-3		1971		3/22/2022	83.9	99.28	FO
Central Florida	Brevard	State Highway Agency	700018	US-192 EB - Sawgrass Creek	US-192 EB	5,150	Sawgrass Creek		1967	2004	2/1/2021	99.7	94.81	
Central Florida	Brevard	State Highway Agency	700023	US-192 WB - St Johns Relief	US-192 WB	5,150	St Johns River Relief		1966	2004	3/1/2021	99.7	90.42	
Central Florida	Brevard	State Highway Agency	700025	SR-528 WB - Sykes Creek	SR-528	15,250	Sykes Creek		1963	2002	3/22/2022	78	77.65	FO
Central Florida	Brevard	State Highway Agency	700026	SR-528 WB - Banana R. Dr.	SR-528 WB	13,000	Banana River Drive		1963		1/27/2022	76.2	90.42	FO
Central Florida	Brevard	State Highway Agency	700027	SR-528 WB-Banana R. Rel.	SR-528	13,000	Banana River Relief		1963		1/31/2022	74.2	92.97	
Central Florida	Brevard	State Highway Agency	700028	SR-528 WB - Banana R.	SR-528	13,000	Banana River		1963		7/27/2020	66.5	87.81	FO
Central Florida	Brevard	State Highway Agency	700029	SR-405 WB - US-1	SR-405 WB	7,550	US-1		1964		12/21/2021	82.3	98.39	
Central Florida	Brevard	State Highway Agency	700030	SR-401 SB - Barge Canal	SR-401 SB	5,750	Service Rd & Canal		1963	2011	9/29/2021	68.8	90.08	FO
Central Florida	Brevard	State Highway Agency	700031	SR-401 SB - Barge Canal	SR-401 SB	4,600	Service Rd & Canal		1963		9/29/2021	77	93.47	FO
Central Florida	Brevard	State Highway Agency	700033	4-12x12x142 CBC	US-192	35,500	Crane Creek		1974		12/21/2021	81.8	94.86	
Central Florida	Brevard	State Highway Agency	700034	I-95 SB - Tillman Canal	1-95 SB	31,250	Tillman Canal		1964	2010	1/7/2021	95.6	91.47	
Central Florida	Brevard	State Highway Agency	700043	I-95 SB -Lake Washington Road	1-95 SB	45,500	Lake Washington Road		1964	2009	1/20/2021	94.5	95.72	
Central Florida	Brevard	State Highway Agency	700046	3-8x4x184 CBC	1-95	91,000	Milner's Canal		1964	1994	1/28/2022	83	95.69	
Central Florida	Brevard	State Highway Agency	700050	2-12x10x187 CBC	1-95	76,435	Rockledge Creek		1965		3/23/2021	72	33.97	
Central Florida	Brevard	State Highway Agency	700052	I-95 SB - SR-520	1-95 SB	41,250	SR-520		1966	2004	1/20/2021	96	96.55	
Central Florida	Brevard	State Highway Agency	700054	I-95 SB - SR-524	1-95 SB	5,100	SR-524		1966	2009	2/21/2022	71	97.28	SD
Central Florida	Brevard	State Highway Agency	700055	3-9x11x157 CBC	1-95	44,500	Santiago Canal		1964		1/19/2021	83	34.18	
Central Florida	Brevard	State Highway Agency	700056	3-10x5x168 CBC	1-95	46,500	Ross Creek		1965	2014	12/16/2020	83	92.43	
Central Florida	Brevard	State Highway Agency	700058	I-95 SB - SR-50	1-95 SB	20,250	SR-50		1965	2013	8/25/2021	97	98.21	
Central Florida	Brevard	State Highway Agency	700059	I-95 SB over SR-406	1-95 SB	20,000	SR-406		1963	2013	8/25/2021	96	98.46	
Central Florida	Brevard	State Highway Agency	700061	Hubert H Humphrey Bridge	SR-520 WB	28,500	Indian River		1966		11/12/2020	71	97.18	FO
Central Florida	Brevard	State Highway Agency	700064	3-8x6x158 CBC	1-95	31,492	Outfall		1967		12/15/2020	83	66.91	
Central Florida	Brevard	State Highway Agency	700065	3-8x8x158 CBC	1-95	31,492	Outfall		1967		12/15/2020	83	66.85	
Central Florida	Brevard	State Highway Agency	700066	I-95 SB - Aurantia Rd.	1-95 SB	15,746	Aurantia Rd.		1967	2014	12/15/2020	94.6	98.42	
Central Florida	Brevard	State Highway Agency	700072	Christa McAuliffe Bridge	SR-3	14,000	Barge Canal		1961	1998	6/24/2021	62:9	97.12	FO
Central Florida	Brevard	State Highway Agency	700074	SR-528 W.B - SR-401	SR-528 WB	13,000	SR-401		1971	2001	10/28/2021	90.3	99.52	
Central Florida	Brevard	State Highway Agency	700075	US-1 SB - SR-404	US-1 SB	19,500	SR-404		1971	1997	10/22/2021	96.5	98.60	
Central Florida	Brevard	State Highway Agency	700076	SR-404 WB - Indian River	SR-404 WB	26,250	Indian River West Relief		1971		10/22/2021	96	89.84	
Central Florida	Brevard	State Highway Agency	700077	SR-404 WB - Indian River	SR-404 WB	26,250	Indian River		1971		5/19/2020	84	95.70	
Central Florida	Brevard	State Highway Agency	700078	SR-404 WB-Indian River	SR-404 WB	26,250	Indian River Relief East		1971		11/3/2021	96	91.74	
Central Florida	Brevard	State Highway Agency	700079	SR-404 WB over CR-3	SR-404 WB	26,250	CR-3		1971		9/17/2021	98	99.44	
Central Florida	Brevard	State Highway Agency	700080	SR-404 WB-Banana River	SR-404 WB	26,500	Banana River Relief West		1971		11/2/2021	98	92.83	
Central Florida	Brevard	State Highway Agency	700081	SR-404 W.B - Banana River	SR-404 WB	26,500	Banana River		1971		5/14/2020	93.9	97.18	
Central Florida	Brevard	State Highway Agency	700082	SR-404 W.B-Banana River	SR-404 WB	26,500	Banana River Relief East		1971		11/1/2021	96	86.95	
Central Florida	Brevard	State Highway Agency	700083	Max K. Rodes	SR-404 WB	26,500	SR-513		1972		10/22/2021	98	97.73	
Central Plonda	Brevard	Tumpike	700084	SR#528 WB St Johns River	SR*528	23,050	St Johns River		1973		8/6/2020	96,9	90.30	
Central Florida	Brevard	Tumpike	700085	SR-407 NB over SR-528 WB	SR-407 NB	4,800	SR-528		1973	1998	8/5/2020	97.3	99.23	
Central Florida	Brevard	Tumpike	700086	4 - 10x10x167 CBC	SR-528	36,500	Ryan's Canal		1973	4007	8/18/2020	70	66.00	
Central Florida	Brevard	Tumpike	700087	SK-528 Wild OVER Pline St.	SK-028 WB	18,250			19/3 T	1997	C 8/5/2020	ᅌᇝᄤᆕᇤᆂᄃ	· n-	
Gentral Florida	Brevard	Tumpike	700089	SR-528 WB over Clear Lk/Inds Rd	SR-528 WB	15,050	SR-524	киа	1973 I O	NAL	84/2020	し K 瞠ー E	: 93-67 E	PAIR
Central Florida	Brevard	Tumpike	700090	SR-407 over Kings Road	SR-407	6,747	Kings Road		1973	1998 -	8/18/2020	9378	99.04	
Gentral Florida	Brevard	Tumpike	700091	SK-407 over I+95	SK-407	6,747	1+95 (SR+9)		1972	1998	$\cap (13/2020)$ V	V ⊏ రో⊤౧		
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PAIR					- inge - 0j 0						ADT=4ver	age Daily Traffie	INN	ESOTA
Renew											SD=Struct	urally Deficient		

# Data cleaning and prep

• 12620 records

- Preprocess raw data
  - Check for outliers and anomalies

Remove records with NBI rating of Functionally Obsolete (FO) or structural deficient (SD)

Handle issues with missing data

Some records missing certain information (e.g., year built, sufficiency rating, etc.)

• Fix formatting issues

"St. Johns" vs "Saint Johns" county

- Data augmentation for enhanced data analytics
  - Humidity

Restore | Renurnose | Renew

- Precipitation
  - Temperature

YEAR ANNIVERSARY

Population density and growth

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Out[	2]:		DIS	TRICT	COUNTY	Unnamed: 2	OWNER	Unnamed: 4	BRIDGE	STRUCTURE NAME	ROADWAY	Unname	d: Unnamed: 8 9	RECONSTR	RUCTED	Unnam
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			1	Central Florida	Brevard	State Highway Agency	NaN	700002	NaN	SR-405 WB - FECRR	SR-405 WE	8 Na	N 7,550		NaN	١
			2	Central Florida	Brevard	State Highway Agency	NaN	700003	NaN	3-7x4x110 CBC	US-1	I Na	N 15,236		NaN	١
			3	Central Florida	Brevard	State Highway Agency	NaN	700006	NaN	US-1 - Crane Cr. & City St	US-1	I Na	N 37,000		NaN	1
			4	Central Florida	Brevard	State Highway Agency	NaN	700007	NaN	US-1 over Elbow Creek	US-1	I Na	N 49,000		NaN	1
						City or										
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Logout

Python 3 (invkernel) C

Not Trusted

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#### Local Data Search

Search State, County, City, Zip Code, or Area Code Search C

#### Population of Counties in Florida (2022)

#### Florida Average Temperature County Rank There are 67 counties in Florida.

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#### A total of 67 results found. Show Results on Map.

USA.com / Ranks / Florida Average Temperature County Rank

Rank	Average Temperature V	County / Population
1.	75.60°F	Miami-Dade, FL / 2,600,861
2.	75.00°F	Broward, FL / 1,815,269
3.	74.96°F	Monroe, FL / 75,208
4.	74.17°F	Palm Beach, FL / 1,359,074
5.	74.06°F	Lee, FL / 647,554
6.	73.95°F	Collier, FL / 334,474
7.	73.73°F	Hendry, FL / 38,360
8.	73.21°F	Martin, FL / 149,658
9.	73.08°F	Sarasota, FL / 386,944
10.	73.06°F	Saint Lucie, FL / 283,988
11.	72.98°F	Manatee, FL / 335,840
12.	72.96°F	Polk, FL / 617,323
13.	72.93°F	Charlotte, FL / 163,151
14.	72.85°F	Hillsborough, FL / 1,279,668
15.	72.85°F	Indian River, FL / 140,918
16.	72.70°F	De Soto, FL / 34,785
17.	72.69°F	Osceola, FL / 289,449
18.	72.66°F	Pinellas, FL / 925,030
19.	72.65°F	Glades, FL / 13,190
20.	72.61°F	Okeechobee, FL / 39,398
21.	72.58°F	Hardee, FL / 27,549
22.	72.53°F	Highlands, FL / 98,261
23.	72.24°F	Brevard, FL / 548,891
24.	71.84°F	Orange, FL / 1,200,241
25.	71.65°F	Hernando, FL / 173,792
26.	71.63°F	Pasco, FL / 472,745
27.	71.29°F	Seminole, FL / 432,135
28.	70.98°F	Sumter, FL / 103,708
29.	70.90°F	Lake, FL / 305,010
30.	70.52°F	Volusia, FL / 498,981
31.	70.35°F	Flagler, FL / 98,843
32.	70.19°F	Citrus, FL / 139,771
	CONCRETE REPAIR Restore   Repurpose   Renew	th

As of 2018, Florida's Miami-Dade County is the most populous county in the Sunshine State, with 2,751,796 residents, representing a population growth of 10.2% since the last census. Miami-Dade is followed by Broward County (1,935,878), Palm Beach County (1,471,150), Hillsborough County (1,381,627), and Orange County (1,323,598) as the only other counties in the state with populations in excess of one million. Of these, Orange County has seen the highest population growth at an impressive 17.7%.

#### Florida Counties with Fewer Residents

The least populous Floridian counties are Liberty County, with 8,242 residents, closely followed by Lafayette County, with its population of 8,451. Both of these counties have seen their populations decline in recent years, with reductions of 1.5% and 4.7%, respectively. However, other counties with small populations, such as Franklin County (11,727) and Glades County (13,754), have had population increases (1.5% for Franklin County and 6.8% for Glades County).

#### Florida Counties with Rapid Growth

Sumter County boasts the highest growth rate in the state, with a substantial increase of 34% according to statistics for 2018, taking its total population to 125,165. Osceola County and St. Johns County also show impressive population growth, with increases of 31.1% and 28.3%, respectively. Bradford County, with its 2010 population of 28,520, has the biggest reduction in numbers – its population has reduced to 26,728, representing a negative growth of -5.2% in the last few years.

			& CSV & JSON
Name	2022 Population 🔻	Growth Since 2010	Density (mi²)
Miami-Dade County	2,723,200	8.63%	1,434.33
Broward County	1,972,790	12.55%	1,634.42
Palm Beach County	1,538,450	16.23%	780.99
Hillsborough County	1,532,120	24.21%	1,501.62
Orange County	1,429,190	24.43%	1,582.16
Duval County	985,064	13.80%	1,291.66
Pinellas County	980,810	7.03%	3,582.30
Lee County	818,898	31.98%	1,044.05
Polk County	779,317	29.22%	433.77
Brevard County	622,159	14.37%	612.70

# jupyter FDOT\_bridge\_info\_data\_pre\_scal\_ack\_tt\_cal\_22 annining etcl topout File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3 (pykernel) C

🖹 🕇 ¾ 🖓 🖪 ↑ ↓ ▶ Run 🔳 C 🗰 Code 🗸 📼

#### In [1]: 1 import numpy as np 2 import pandas as pd

In [2]: N 1 FBI\_df=pd.read\_csv('FDOT\_Florida Bridge Information.csv', skip\_blank\_lines=True)
2 FBI\_df

Out[2]:		DISTRICT	COUNTY	Unnamed: 2	OWNER	Unnamed: 4	BRIDGE	STRUCTURE NAME	ROADWAY	Unnamed: 8	Unnamed: 9	 RECONSTRUCTED	Unnamed: 15
	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN
	1	Central Florida	Brevard	State Highway Agency	NaN	700002	NaN	SR-405 WB - FECRR	SR-405 WB	NaN	7,550	 NaN	NaN
	2	Central Florida	Brevard	State Highway Agency	NaN	700003	NaN	3-7x4x110 CBC	US-1	NaN	15,236	 NaN	NaN
	3	Central Florida	Brevard	State Highway Agency	NaN	700006	NaN	US-1 - Crane Cr. & City St	US-1	NaN	37,000	 NaN	1990
	4	Central Florida	Brevard	State Highway Agency	NaN	700007	NaN	US-1 over Elbow Creek	US-1	NaN	49,000	NaN	1990
				City or									

In [3]: M 1 Nan\_rowindx\_list=FBI\_df.index[FBI\_df['DISTRICT'].isnull()].tolist() # find empty (Nan) row indices
2 header\_rowindx\_list=FBI\_df.index[FBI\_df['DISTRICT']=='DISTRICT'].tolist() # find header row indices
3 drop\_indx\_list=Nan\_rowindx\_list+Neader\_rowindx\_list

#### In [4]: H 1 FBI\_df=FBI\_df.drop(drop\_indx\_list) # drop empty and intermediate header rows

[5]: N	1	# fix column names									
	2	<pre>FBI_df = FBI_df.rename(columns={'OWNER': 'del_1', 'Unnamed: 2': 'OWNER'})</pre>									
	3	<pre>FBI_df = FBI_df.rename(columns={'Unnamed: 4': 'BRIDGE', 'BRIDGE': 'del_2'})</pre>									
	4	<pre>FBI_df = FBI_df.rename(columns={'Unnamed: 9': 'ADT', 'ADT': 'del_3','Unnamed: 8': 'del_4'})</pre>									
	5	<pre>FBI_df = FBI_df.rename(columns={'Unnamed: 12': 'YEAR BUILT', 'YEAR BUILT': 'del_5'})</pre>									
	6	<pre>FBI_df = FBI_df.rename(columns={'Unnamed: 15': 'RECONSTRUCTED', 'RECONSTRUCTED': 'del_6'})</pre>									
	7	<pre>FBI_df = FBI_df.rename(columns={'Unnamed: 16': 'LAST INSPECTION', 'LAST INSPECTION': 'del_7'})</pre>									
	8	<pre>FBI_df = FBI_df.rename(columns={'Unnamed: 19': 'SUFFICIENCY RATING', 'SUFFICIENCY RATING': 'del_8'})</pre>									
	9	<pre>FBI_df = FBI_df.rename(columns={'Unnamed: 20': 'HEALTH INDEX', 'HEALTH INDEX': 'del_9'})</pre>									
	10	<pre>FBI_df = FBI_df.rename(columns={'Unnamed: 23': 'del_10'})</pre>									
	11	# remove Nan columns									
	12	<pre>FBI_df=FBI_df.drop(columns=['del_1','del_2',</pre>									
	13	'del_3','del_4',									
	14	'del_5','del_6',									
	15	'del_7','del_8',									
	16	'del 9', 'del 10'])									
	17	FBI df									

5]:		DISTRICT	COUNTY	OWNER	BRIDGE	STRUCTURE NAME	ROADWAY	ADT	FACILITY	YEAR	RECONSTRUCTED	LAST INSPECTION	SUFFICIENCY RATING	HE
	1	Central Florida	Brevard	State Highway Agency	700002	SR-405 WB - FECRR	SR-405 WB	7,550	FECRR	1969.0	NaN	11/9/2021	80.3	
	2	Central Florida	Brevard	State Highway Agency	700003	3-7x4x110 CBC	US-1	15,236	Kid Creek	1964.0	NaN	4/3/2020	69.0	
		Central		State	700000	US-1 - Crane			City St. &			10.00.000.0		

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### OUTLINE

- Introduction
- Background
- Definitions of artificial intelligence (AI) and machine learning (ML)
- Potential application of AI/ML for asset management
- Potential application of AI/ML for health monitoring
- Conclusions



# **Possible future of health monitoring**













#### **Damage Conditions Distribution**



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"The system flags many defects that even our team of trained engineers would have easily missed" "This technology saves us a phenomenal amount of time and effort"

"T2D2 is the future of structural inspections. This should be the way all structures are inspected"





![](_page_30_Figure_0.jpeg)

![](_page_31_Figure_1.jpeg)

![](_page_31_Picture_2.jpeg)

![](_page_32_Figure_0.jpeg)

![](_page_33_Figure_0.jpeg)

![](_page_34_Figure_0.jpeg)

### Half-cell reference electrode embedded into concrete

![](_page_35_Picture_1.jpeg)

![](_page_35_Picture_2.jpeg)

Multi-probe device consisting of four black steel bars acting as anodes and a noble metal as the cathode

![](_page_35_Picture_4.jpeg)

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![](_page_36_Figure_0.jpeg)

### OUTLINE

- Introduction
- Background
- Definitions and examples of artificial intelligence and machine learning
- Potential application of machine learning for asset management
- Discussion on how innovation may impact future of bridge monitoring
- Conclusions

![](_page_37_Picture_7.jpeg)

### **DATA-DRIVEN PREVENTIVE MAINTENANCE**

![](_page_38_Figure_1.jpeg)

### PREVENT RATHER THAN REACT

![](_page_39_Figure_1.jpeg)

![](_page_39_Picture_2.jpeg)

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# \_Will Bridge DIGITAL TWINS be the future?

![](_page_40_Figure_1.jpeg)

# **Questions?**

![](_page_41_Picture_1.jpeg)